DESIGN AND DEVELOPMENT OF SENTIMENT ANALYSIS MODEL FOR DETECTING DEPRESSION DURING COVID-19 USING MACHINE LEARNING ALGORITHMS

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Computer Science and Engineering

By

Sofia

Registration Number: 41900081

Supervised By

Dr. Arun Malik (17442)

School of Computer Science and Engineering (Associate Professor)

Lovely Professional University

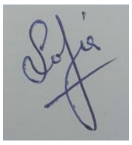
Transforming Education Transforming India

LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

2023

DECLARATION

I, hereby declared that the presented work in the thesis entitled "Design and Development of Sentiment Analysis Model For Detecting Depression During Covid-19 Using Machine Learning Algorithms" in fulfilment of degree of Doctor of Philosophy (Ph. D.) is outcome of research work carried out by me under the supervision Dr. Arun Mailk, working as Associate Professor, in the School of Computer Science and Engineering of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



(Signature of Scholar)

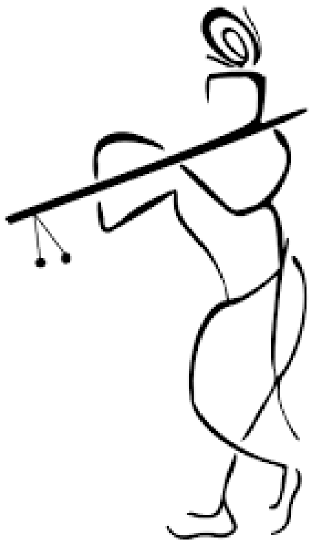
Name of the scholar: Sofia
Registration No.: 41900081
Department/school: Computer Science and Engineering
Lovely Professional University,
Punjab, India

CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "Design and Development of Sentiment Analysis Model For Detecting Depression During Covid-19 Using Machine Learning Algorithms" submitted in fulfillment of the requirement for the reward of degree of Doctor of Philosophy (Ph.D.) in the School of Computer Science and Engineering, is a research work carried out by Sofia, 41900081, is bonafide record of her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

Arun Malik

(Signature of Supervisor)
Name of supervisor: Dr. Arun Malik
Designation: Associate Professor
Department/school: Computer Science and Engineering
University: Lovely Professional University



"The aim of life is inquiry into the Truth ..."

– Bhagavata Purana

∼ dedicated to my family ∼

ACKNOWLEDGEMENT

First and foremost, I am grateful to God for granting me the chance and strength to do this task successfully.

I would like to express my gratitude to my excellent Ph.D. advisor, Dr. Arun Malik, for his important supervision, support, and guidance. I owe a profound sense of gratitude to the vibrant academician and generous mentor, who has been a tremendous source of motivation for me throughout the completion of this project. They truly made an effort to interact with me academically. As a true experimentalist, there is a rational style of thinking that offered a solid foundation for future undertakings.

My parents have my deepest thanks and debt for their blessings, encouragement, and support. My siblings should be commended for their cooperation and understanding.

Lastly, I would like to gratefully thank my valued Supervisors for their assistance during this project. I am grateful to the esteemed HOD, Dr. Parul Khurana, for his prompt assistance and helpful direction. I'd like to thank all the writers whose works were cited in this study.

Date: November 9, 2023 Sofia

Abbreviations

Abbreviations	Description
SVM	Support Vector Machine
DT	Decision Tree
NB	Naive Bayes
KNN	K-Nearest Neighbour
ML	Machine Learning
RBI	Reserve Bank of India
IOT	Internet of Things
NLP	Natural Language Processing
EHR	Electronic Health Record
DASS	Depression Anxiety and Stress Scale
AI	Artificial Intelligence
BDI	Beck Depression Inventory
HAM-D	Hamilton Depression Rating Scale
MADRS	Montgomery-Asberg Depression Rating Scale
SPSI-RTM	Social Problem-Solving Inventory-Revised
BASC	Behaviour Assessment System for Children
CBCL	Child Behaviour Checklist
BHS	Beck Hopeless Scale
QID-SR	Quick Inventory of Depressive Symptomatology-Self Report
PHQ-9	Patient Health Questionnaire
RFS	Reminiscence Functions Scale

SF-36	Short Form Health Survey
SAS-SR	Social Adjustment Scale-Self Report
SFQ	Social Functioning Questionnaire
GDS	Geriatric Depression Scale
LSI	Life Satisfaction Index

ABSTRACT

COVID-19 harmed the lives of people in every region of the world. It has been established that, in addition to the physical symptoms, it significantly influences the patient's mental health. Depression has been identified as one of the most widespread disorders that can hasten a person's mortality at an early age. This is one of the conditions that has been singled out for this distinction. The trajectory of life for millions of people has been altered as a result of this illness. We conducted a survey that consisted of 21 questions based on the Hamilton instrument and the advice of a psychiatrist. This was done so that we could continue forward with the inquiry into the identification of depression in individuals.

After the data were compiled and analysed, it became clear that people younger than 45 years of age had a higher risk of suffering from depression when compared to those older than 45 years of age. This is because most people at this age are concerned about getting married or schooling their children. On the other side, research has revealed that those whose ages fall between 18 and 25 are also at an increased risk of suffering from depression. This is likely because, at this stage in their lives, these individuals are more conscious of the potential outcomes of their lives. Based on all of the replies received, the findings of the survey were put through several different machine learning algorithms, including Decision Tree, KNN, and Naive Bayes. These algorithms were used to analyse the results.

Further investigation is being done into how these two techniques are similar to and different from one another. According to the findings of the research, KNN has produced better results than other approaches in terms of accuracy, whereas decision trees have produced better results in terms of the amount of time needed to detect depression in a person. In conclusion, to overcome the traditional approach to a depression diagnosis, which is made up of affirmative questions and constant feedback

from individuals, a model that is based on machine learning is offered as a potential alternative.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

In general, pandemics are not only a major burden for public health, but they also pose substantial social, economic, and political challenges in the nations in which they occur. Pandemics can be caused by several different viruses. COVID-19 is not only considered as the greatest threat to international public health in this century but it is also seen as a symptom of unfairness and a lack of social progress. In other words, COVID-19 is a sign that this century is failing to make social progress. The letters 'CO', 'VI', and 'D' in the name COVID-19 each stand for the corresponding terms 'corona', 'virus,' and 'disease,' while the number 19 refers to the year in which the disease was first identified. Coronaviruses have a diameter that spans from 80 to 120 nanometers, and they are RNA viruses that only have one strand in their genome. In December 2019, it was announced that Wuhan, which is situated in the Hubei area of China, had seen the very first modern outbreak of COVID-19. The majority of the initial cases could be traced back to an infection that was spread through a seafood market as the point of origin. Since then, the sickness has alarmingly spread around the globe, and it has now arrived on every continent other than Antarctica. The only continent it has yet to reach is Antarctica. More than two hundred countries and regions, including China, Italy, Iran, South Korea, India, Switzerland, Taiwan, the United States of America, Sweden, Singapore, Sri Lanka, France, Australia, Malaysia, Spain, the United Kingdom, Nepal, Finland, the Netherlands, Belgium, Russia, Thailand, the Philippines, and Cambodia, have reported confirmed cases of COVID-19. After making landfall in China in January 2020, the COVID-19 virus soon expanded to other countries, including South Korea, Iran, and Italy, where it was responsible for substantial outbreaks towards the end of February and the beginning of March 2020. The number of people who are infected with COVID-19 in Spain is higher than the number of patients in the United States of America, which puts the United States of America at the top of the list.

Number of people died in the US as a result of this illness. According to information made public by the Chinese government and the WHO, the current outbreak has resulted in the infection of 84,180 persons in China, and as of April 18, the outbreak has claimed the lives of more than 4642 people. On January 30, 2020, the Thrissur district of Kerala reported the first case of the coronavirus epidemic in India. The incident happened following the return home of a student who had been attending Wuhan University in China. India's Ministry of Health revealed on April 18, 2020, that there had been 14,378 confirmed instances of coronavirus infection nationwide, along with 480 fatalities. The virus has a very high rate of transmission, which is to blame for its widespread distribution worldwide. On the other hand, the growth of international travel and tourism and the resulting improvement in accessibility may also be a factor in the virus's continued worldwide spread. Numerous nations throughout the world hold a wide range of annual mass gathering festivals that fall under the political, religious, socio-cultural, or scientific categories. These kinds of huge gatherings have a long history of being linked to disease outbreaks on both the local and global levels, and they are likely to worsen a lot of the risk factors related to COVID-19. The potential of a global pandemic is posed by the emergence of COVID-19 in Asia and its subsequent spread to other parts of the world, including the Americas, Africa, and Europe. [1]

1.1 Impact of Covid-19

Regardless of the severity of the virus's effect on the populations of various countries, it has had a significant negative effect on both the global and national economies. The unique coronavirus does not respect national boundaries or religious beliefs, and it has spread across all social classes. It has a high potential for spreading to other people and is difficult to anticipate. The world has never been prepared for a pandemic of this kind, and now we are in a race against time to create a vaccine to stop its further spread. The newly discovered COVID-19 showed signs of being highly contagious and rapidly disseminating around the world. (see Figure 1.1). As

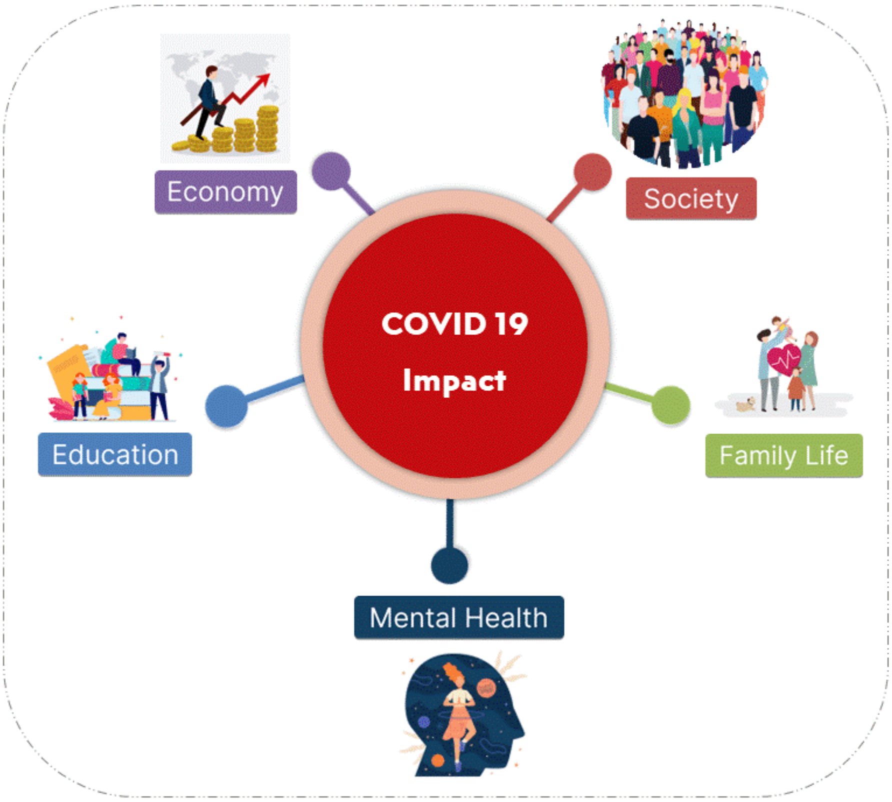


FIGURE 1.1: *Covid-19 Impact.*

of April 3rd, 2020, there had been a minimum of 52,869 deaths and a total of 10,066 confirmed cases of coronavirus infection. On May 18, 2020, the number of confirmed cases reached 46,79,511, with 3,15,005 people losing their lives. These numbers are subject to continual change. The novel coronavirus spreads in phases, with stage 1 including imported cases, stage 2 involving local transmission, stage 3 involving community transmission, and stage 4 (out-of-control transmission). "Transmission" refers to the transfer of microorganisms from one infected individual to another uninfected person when addressing the spread of disease among humans. Microorganisms can migrate through direct contact with surfaces, through droplets, or by indirect contact with surfaces, such as surface contamination. The incubation period refers to the amount of time that passes between a person becoming infected with a virus and the onset of the disease's symptoms. It can be anywhere from one to fourteen days for COVID-19, but the average is closer to five days. Fever, exhaustion, and a dry cough are the three symptoms of COVID-19 that are seen most frequently. Some people can experience aches and pains, a stuffy or runny nose, a sore throat, diarrhea, or congestion in the nasal passages. These symptoms are often modest, and their onset is slow and steady. Some people contract the infection, but they don't have any symptoms or feel sick. The vast majority of patients (about 70 percent) recover from the illness without requiring any kind of specialized therapy. A person infected with COVID-19 has roughly 1 in 6 chances of becoming gravely ill and having trouble breathing after becoming infected with the virus. People who are older or who already have an underlying medical condition, such as diabetes, high blood pressure, or heart difficulties, have a greater risk of developing a serious illness.

The unprecedented lockdown, which has had a significant negative impact, has severely hurt the economy. At this point, the jobs and ways of life of millions of people are in jeopardy. Since state borders were closed, more than fifty million migrant workers either returned to their homes in their home villages or relocated to camps inside major cities. They were left without a job or a source of income as a result of this as activities all around the country ceased. The majority of them have not yet returned, which has had a considerable impact on the labor pool in urban areas. There have been reports of some of them coming to cities in quest of jobs and other means of support. Additionally, there were significant restrictions placed on the movement of unprocessed materials as well as finished goods between states. Because countries have closed their national borders, there has been an abrupt halt in the movement of goods and people across international frontiers. All of these factors are causing serious disruptions in the supply mechanisms and distribution chains of nearly every industry. At the same time, there has been a complete collapse of consumption demand as a result of the fact that millions of people are staying inside and delaying the expenditure of money on things that are not needed.

How long and severe the health crisis lasts, how frequently lockdowns are required in various sections of the nation, and how things turn out once the statewide lockdown is released and normal economic activity can resume will all affect how bad the pandemic is overall. Up until now, the economy has suffered a great deal of harm. This crisis happens when India's GDP growth slows and unemployment is rising as a result of the country's dismal economic performance over the past few years. The economy was already in a fragile situation before the shock, therefore it's probable that this will make the shock's effects worse. This is especially true because the financial sector, which is the brain of the economy, has not been operating efficiently, and because there is very little room for policy in the macroeconomic realm to respond to such a crisis. In the past, the Indian economy was mostly suffering from a slowdown in demand, but in recent times, both demand and supply have been impacted by the disruption. There are four different ways in which the influence is transmitted to output growth. These include a decline in domestic demand and a disruption of the domestic supply. Global recession and supply chain disruptions are to blame for external supply and demand limitations. The economic shock is affecting both the formal and informal economies. It might take a long time for the economy to recover from the shock created by this incident, even if the lockdown is lifted in August or September of 2020. The government's and the Reserve Bank of India's (RBI) actions taken in reaction to the situation will, to a considerable extent, determine the extent to which the economy will recover. The decision-makers in government have already disclosed the first set of actions that will be taken. There is still a significant amount of work that needs to be completed before the shock effects on the economy can be reduced.

1.1.1 Impact on society

All segments of the population have been impacted by the COVID-19 outbreak, but those in the social groupings that are now most at risk have been particularly hard hit. The outbreak is still affecting populations, including those who are currently living in situations of poverty. Homeless people, for example, are more likely to contract the virus because they may not be able to find a safe place to shelter during an outbreak. Youth have been urged by a variety of governments to get involved in the fight against threats to both themselves and the general community. Additionally, young people are in a position to assist those who are most helpless and to contribute to the expansion of public health and social awareness initiatives within their communities. Therefore, young people are extremely important in controlling the virus's spread and mitigating the effects it will have on public health, society, and the economy in general. A new routine for surviving and a new strategy for interacting with those who are closest to you are developed as a result of social distance, which is more accurately described as physical distance. In reality, it is causing distance to grow between friends and relatives. On the other hand, technologies such as mobile phones and the internet are bringing individuals into closer proximity with one another. People are gradually getting used to the idea that they can stay at home and are developing new routines to keep themselves interested in professional work as opposed to household duties. Because COVID-19 is locked down, there is a restricted amount of consumption of the available resources. People have realized that their requirements for survival are extremely minimal, but that they have been wasting resources to achieve status in society. I'd say that the government shutdown is giving us the chance to discover how to achieve the Sustainable Development Goals (SDGs) in a very concrete way. Because of anthropogenic activity, the world economy has been shut down, allowing the planet to heal and regenerate itself.

1.1.2 Impact on family-life

The members of the family have become closer as a result of being cooped up indoors and required to work from home. They are coerced into engaging in activities such as talking, eating, and playing together daily, which is something that the majority of the families are unable to do owing to work and other responsibilities. When one had to leave the house early and return at strange hours, frequently when the kids were sleeping, family life's rhythm was upset. Occasional reports claimed that some of the kids may only see their fathers once a week or twice a month due to their fathers' busy schedules. Therefore, it would seem that the lockdown is advantageous for social engineering and family life. People who work from home and stay at home continuously obtain the full amount of sleep they need for optimal health and happy functioning. It is commonly believed that getting sufficient sleep will strengthen one's immune system. Because they do not have to spend time commuting to and from the office, they can put in additional hours of work, which results in increased effectiveness and output. Second, people can conserve gasoline and contribute to the reduction of pollutants in the air. Thirdly, there is no stress associated with traveling, which results in increased productivity. As a result of the COVID-19 epidemic, lockdowns have been implemented in several nations, which have been linked to an increase in domestic violence and violence between intimate partners. As a result of financial insecurity, stress, and uncertainty, there has been an increase in domestic violence. Abusers can exert a significant degree of influence over their victims' day-to-day lives. [2].

1.1.3 Impact on economy

The unprecedented lockdown, which has had a significant negative impact, has severely hurt the economy. At this point, the jobs and ways of life of millions of people are in jeopardy. Since state borders were closed, more than fifty million migrant workers either returned to their homes in their home villages or relocated to camps inside major cities. They were left without a job or a source of income as a result of this as activities all around the country ceased. The majority of them have not yet returned, which has placed a severe strain on the labor pool in urban areas, despite rumors that some of them are returning to the cities at this time in search of work and other means of subsistence. Additionally, there were significant restrictions placed on the movement of unprocessed resources as well as finished items between states. Because countries have closed their national borders, there has been an abrupt halt in the movement of goods and people across international frontiers. All of these factors are causing serious disruptions in the supply mechanisms and distribution chains of nearly every industry. Because millions of people are staying indoors and avoiding the purchase of unnecessary items, there has been a full collapse in consumption demand at the same time.

The length and severity of the health crisis, the frequency with which lockdowns are required in various sections of the nation, and the circumstances surrounding the lifting of the statewide lockdown and the return of normal economic activity will all determine how awful the pandemic is overall. Up until this time, the economy has sustained severe harm. The timing of this crisis coincides with declining GDP growth in India and rising unemployment as a result of the country's dismal economic performance over the past few years. The effect of the shock may be made worse as a result of the vulnerable state that the economy was in before being struck by this shock. This is especially true because the financial sector, which is the brain of the economy, has not been operating efficiently, and because there is very little room for policy in the macroeconomic realm to respond to such a crisis. In the past, the Indian economy was mostly suffering from a slowdown in demand, but in recent times, both demand and supply have been impacted by the disruption. There are four different ways in which the influence is transmitted to output growth. These include a decline in domestic demand and a disruption of the domestic supply. Global recession and supply chain disruptions are to blame for external supply and demand limitations. The economic shock is affecting both the formal and informal economies. It might take some time for the economy to recover from the shock created by this occurrence, even if the lockdown is removed in August or September of 2020. The Reserve Bank of India's (RBI) and the government's responses to the crisis will play a significant role in determining how quickly the economy can recover. The decision-makers in government have already disclosed the first set of actions that will be taken. There is still a significant amount of work that needs to be completed before the shock's effects on the economy can be reduced. [3].

1.1.4 Impact on higher education

A common tendency that has evolved in reaction to the pandemic in educational systems around the world is the establishment of "emergency e-learning" protocols. The influence on higher education has been significant and instructive. These protocols signify the quick switch from traditional classroom settings to online learning platforms. Educational institutions are having a difficult time adapting to this transition while simultaneously attempting to choose the best technology and teaching strategies for their students. The abrupt shift from in-person, face-to-face education to teaching delivered remotely and the shutting of the campus are only the first little steps in the long journey towards offering online education, which will include strong tools for student involvement and instructor training. After the pandemic is over, this might open the way for closer relationships between universities, corporations that provide online education, and technology service providers. To ensure that the process of teaching and learning goes off without a hitch at the universities, substantial attention will need to be paid to the training and equipping of educators with digital technology. To improve educators' capacity to teach, the government will need to take the initiative and commit to maintaining programs for continuing education and professional development. The pandemic has brought to light the vulnerabilities and deficiencies of the existing education systems. Additionally, it has highlighted the need for both developed and developing nations to increase their levels of digital literacy, especially in these trying times. After the outbreak, it's conceivable that a stronger focus on the digitalization of educational services and communication will become the norm. Long-held beliefs about the role of higher education institutions in the delivery of quality education, as well as the mode of delivery, accessibility, the significance of learning that continues throughout one's life, and the educators' perceptions of the types of students who attend their classes, have been called into question by the current situation. It's feasible that this may provide educators and decision-makers with important information that will help improve education systems globally. [4].

Due to how much teachers relied on e-learning during the flu pandemic and how well they were able to adapt to it, there may be a trend towards adding more online components to classroom lessons. This, however, creates a lot of logistical problems and limits, especially when it comes to how easy it is to use digital technology to teach. The phrase "digital inequality" describes a large divide that exists in contemporary society. One cannot fairly assume that all instructors and students will have access to sophisticated devices connected to the internet and be able to communicate with one another outside of their university.

Students who come from economically disadvantaged backgrounds face a bigger burden due to the high cost of eLearning, which is another factor that restricts access to this kind of education. It can have a significant impact on students in higher education institutions if the government does not establish regulations that are supportive of students and ensure that the Internet is affordable and simple for them to use. Students have a much better opportunity to exchange knowledge and ask for assistance since face-to-face communication is more beneficial to the learning process. It is also simpler and more interactive. Students who learn remotely face a variety of difficulties that they must overcome. There is less of a sense of belonging and community among the students in a virtual classroom. When there is no teacher present to offer hands-on assistance, students who are less able to self-regulate or study alone have a harder time in class. The use of online films, digital content, and discussion forums might not produce a comprehensive teaching and learning process. The consequences for privacy and surveillance of requiring hundreds of millions of children to use commercial software that has not been adequately tested and approved for educational purposes worry several civil rights organizations and activists. These issues arise from the software's lack of thorough testing and approval for educational use.

The sudden shift to adapting and implementing online learning has increased the burden and stress on the teaching personnel. The procedures used by educators to prepare curricula, produce electronic content, test students, and provide reports need to be reviewed because it's possible that these processes weren't built with enough planning and consideration. Educators should be given professional autonomy, trusted with their judgments, and ensured clear and compassionate communication with all stakeholders in the higher education system to achieve better-focused learning outcomes and develop effective methods of eLearning. This will assist in achieving the objectives of more efficient eLearning techniques and targeted learning results. [5].

1.1.5 Impact on mental health

Every nation's well-being depends in large measure on its level of health. The COVID-19 pandemic's occurrence is an unanticipated jolt to the economy. The economy was already in terrible shape before COVID-19 hit. An unexpected disease epidemic could make people anxious. It is quite difficult to identify a disease in its early stages. To prevent it from spreading in a region, action is required. People express their views, opinions, and emotions through posts on social networking websites. The study of people's emotions, attitudes, and views is known as sentiment analysis. This study includes a section on depression to categorize a person as depressed or not based on their posts on Facebook, Instagram, Twitter, blogs, and forums [6].

Electronic information is currently advancing quickly in every aspect of life, creating a significant volume of data. As a result, a lot of data is produced in the business, healthcare, tourism, e-marketing, and other industries. Automated analysis systems deal with the efficient storing of huge amounts of data as well as the analysis, summarization, and classification of data. Sentiment analysis is a method used for opinion mining across a variety of disciplines, including machine learning, information retrieval, statistics, and computational linguistics. Nowadays, social networking has developed into a community and is one of the most popular categories of online activity. It provides a location for online connections. People can communicate their opinions, feelings, impressions, and thoughts with one another through using social networking sites like Twitter, Facebook, blogs, and forums. Using these postings, tweets, and forums, one can assess or define the decisions made by individuals. The term "analyzing sentiment" refers to the analysis of various perceptions, ideas, sentiments, and emotions. Finding and classifying the emotions that individuals express on social networking sites is the goal of sentiment analysis.

Natural language processing is used for text exploration in sentiment analysis, and statistics are used to determine human sentiment. This approach breaks down the analysis of sentimental data into five distinct steps. (see Figure 1.2) -

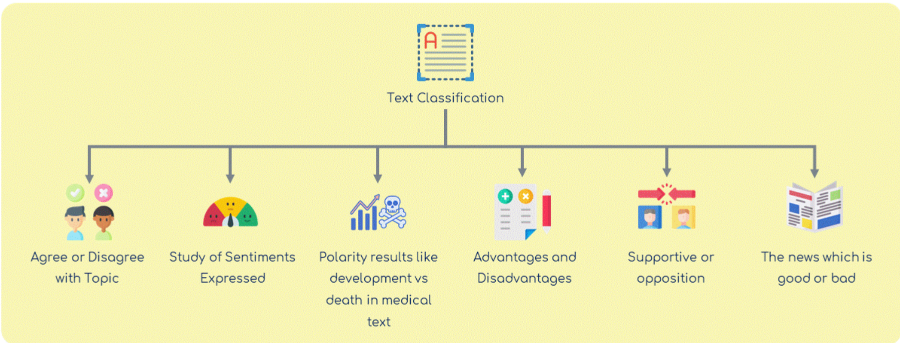


FIGURE 1.2: *Criteria of text classification.*

1. Data gathering from social networking sites is the initial step in the analysis of the emotional data. The use of language, writing, etc., conveys this information in a variety of ways. For extraction and classification, natural language analysis and text mining are also used.

2. The second step is cleaning the extracted data so it is ready for analysis. Text preparation is the procedure involved.

3. The emotion is located in the data at the third stage of sentiment analysis. This analyses the remarks and opinions from the sentences that were extracted. Thoughts, values, and opinions are examples of sentences that are subjective. On the other side, facts and dependable knowledge are examples of phrases that are objective.

4. The classification of sentiments is the next stage in sentiment analysis. The subjective sentences are categorized according to their polarity, which might be positive, negative, or neutral.

5. The output of this analysis is presented as the final step. A sentiment analysis' principal objective is to transform vague material into helpful information. Following analysis, the findings are presented as graphs, including pie charts, bar charts, and line graphs.

1.2 Introduction to Depression

People publish on social networking sites to express their opinions, feelings, and thoughts. An examination of people's emotions, feelings, opinions, etc. is known as sentiment analysis. This study uses posts on Facebook, Instagram, Twitter, blogs, and forums to assess whether or not a person is depressed. Depression is also included in this study. (see Figure 1.3).

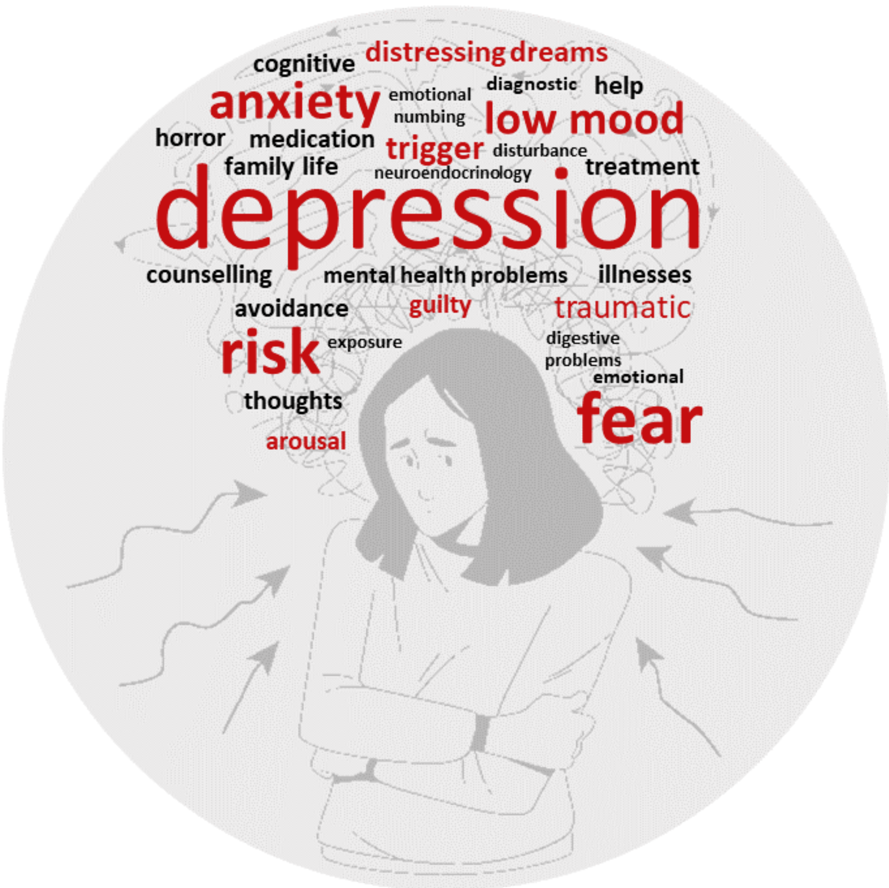


FIGURE 1.3: *Depression.*

A depressed individual experiences different bodily and mental problems is constantly gloomy, tense, and hopeless, and loses interest in daily activities. One of the important societal challenges that is spreading rapidly is depression. Many people have this illness, yet only a small percentage of them receive therapy. After anxiety, depression is the second most prevalent mental health issue worldwide. Suicide is a result of depression. Depression is the primary cause of suicide among young people. (see Figure 1.4). Every day, a depressed person experiences sadness, tension, and

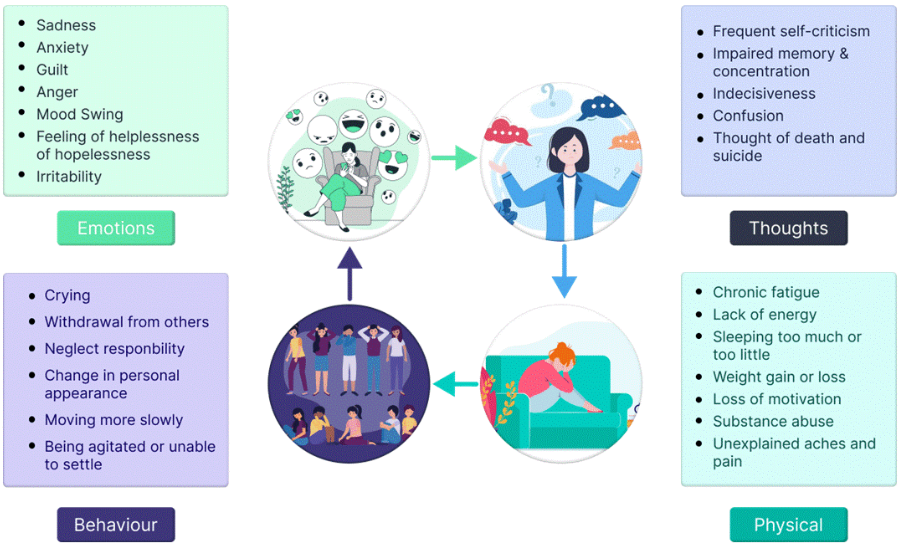


FIGURE 1.4: *Signs and symptoms of depression.*

hopelessness. They develop a variety of physical and mental issues and lose interest in routine activities. One of the most significant social issues that is only becoming worse over time is depression. Many people have this illness, yet only a small percentage of them receive therapy. After anxiety, depression is the second most prevalent mental health issue worldwide. Suicide is a result of depression. Depression is the primary cause of suicide among young people.

A lifestyle with less physical labor may result from the growing usage of technology. A person may also be more susceptible to developing a mental condition if they are under constant stress. Peer pressure, heart attacks, depression, and a host of other negative effects are examples of these vulnerabilities. Several approaches to diagnosing depression are carefully examined. The mechanisms include the use of questionnaires addressed to the individual, social media posts, text used in spoken conversation, and facial expressions to collect data. The information that was gathered serves as the basis for the outcome. Whether or whether the person needs attention is the predicted outcome in this scenario. In the framework of this research project, a variety of machine learning techniques and classifiers, including decision trees, SVM, Naive Bayes classifiers, logistic regression, and KNN classifiers, are investigated to determine the degree of mental health within a certain population. One of the target groups used in this identification technique is the general population, which includes high school, college, and working-age individuals [7].

1.3 Introduction to Machine Learning

Building a model that describes the relationship between one set of observable quantities (inputs) and another group of variables that are connected to these (outputs) is the main objective of a huge variety of scientific domains. The values of the important variables can then be determined by observing and recording the pertinent observables after such a mathematical model has been constructed. Unfortunately, many real-world occurrences are too complex to be directly modeled as a closed-form input-output relationship. A computational model of these complex relationships can be automatically built using machine learning techniques. This is achieved by processing the easily accessible data and optimizing a performance criterion that is unique to the solution. (see Figure 1.5).

The process of automatically creating a model is known as ”training,” and the information that is used during training is known as ”training data.” The trained model can be used to predict new input values that weren't part of the training data as well as to provide new insights into how the input variables translate to the output. Machine learning algorithms frequently need a large amount of training data to be able to learn an appropriate model [8]. Therefore, a crucial first step in the implementation of machine learning techniques is the collection of a large number of representative training instances and the storing of this data in a format that is

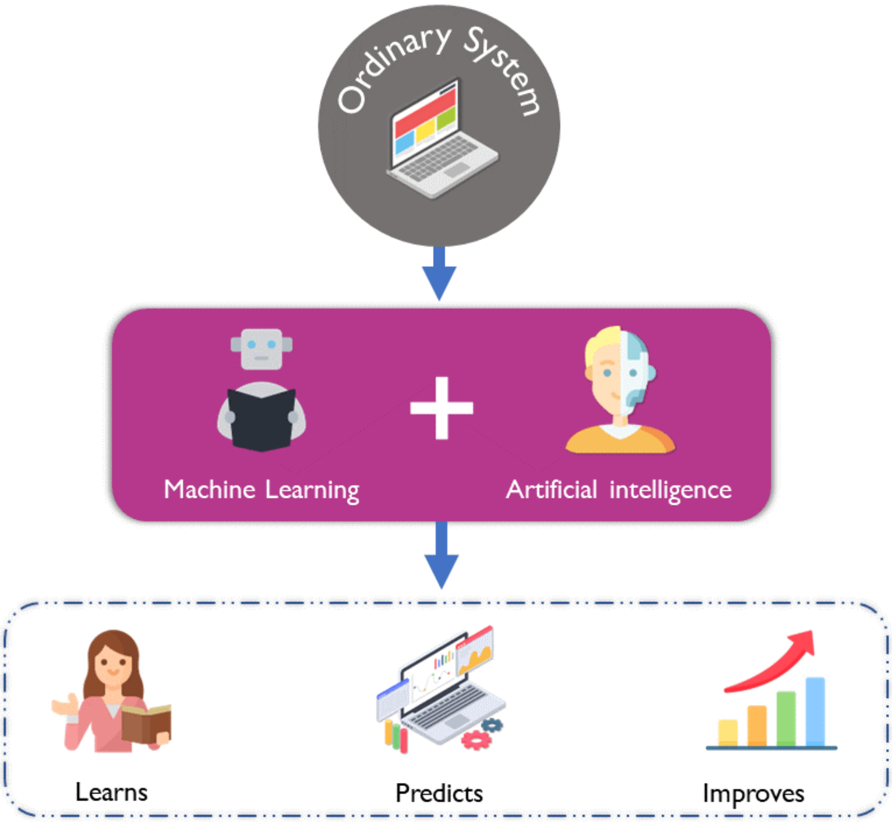


FIGURE 1.5: *Machine learning.*

suitable for computing needs. Machine learning can now be used in a wide range of industries, including bioinformatics, chemical informatics, social network analysis, stock market analysis, robotics, and medical diagnostics. Recent advancements in the capacity for the gathering, storage, and processing of digital data have made this possible. There are often multiple computational models that can be trained to handle any given machine-learning task. Unfortunately, choosing an algorithm or model does not have a single set of guidelines.

A model's performance depends on a wide range of variables, such as the quantity and quality of training data, the complexity and structure of the relationship between the input and output variables, and computational limitations like the amount of memory and training time available. To identify the models and algorithms that are most suited to solve the given problem, it is frequently required to evaluate a wide range of alternative models and approaches. Everyone benefits from the availability of common software packages that combine a variety of algorithms into a single framework. Once the accessible data has been properly arranged, these packages make it much easier to experiment with the various options. [9].

”Supervised learning” refers to learning that takes place under supervision or guidance. The goal of this kind of learning is to learn how to map one area to another, and the ”training set” is made up of matched sets of input and expected output. Applications include the previously mentioned channel decoder in addition to the classification of email spam based on examples of spam emails and emails that are not spam.

Unsupervised learning techniques just require the training data’s input attribute values, and a learning algorithm makes use of those feature values to find hidden patterns. This category includes clustering techniques that aim to organize the data into logically related groups. These techniques are used in the field of bioinformatics for a range of problems, such as gene expression analysis and the use of microarrays. In general, operations that typically include clustering include the analysis of market segments, in which people are classed according to their social behavior, and the classification of publications according to their topic matter. [10].

Support vector machines, Nave Bayes, decision trees, and K-Nearest Neighbour are on the list of learning algorithms that are most frequently employed.

The Naive Bayes classifiers, which are widely used in machine learning for text classification, are based on the conditional likelihood of features belonging to a class, with the features being selected using feature selection techniques. The use of supplementary characteristics is suggested in this paper. This is accomplished by selecting an auxiliary feature that can reclassify the text space in the direction of the chosen features after initially determining features using a recognized method for feature selection. The relevant conditional probability is changed to increase the classification process’ level of accuracy. Illustrative examples have been used to show that the proposed technique does improve the functionality of the naive Bayes classifier.[11].

One of the most successful machine learning methods is the Support Vector Machine or SVM. It was initially introduced in the 1990s and is mostly used for pattern recognition. This has also been used to address a wide range of pattern classification-related problems, including face recognition, speech recognition, text categorization, picture recognition, and many others. When it comes to categorizing data based on either prior knowledge or statistical information gleaned from raw data, pattern recognition is an effective method. This approach is employed in many different academic domains. A supervised machine learning example is the Support Vector Machine (SVM). An SVM training method builds a model that predicts the category that a new example will fall under using a set of training examples, each of which is identified as belonging to one of the numerous categories. The SVM is better able to generalize problems, which is the goal of statistical learning. [12].

In the world of data mining, the decision tree method is frequently employed. It can be used to set up classification systems based on numerous covariates or to develop prediction algorithms for a target variable. Using this technique, a population is divided into sections that resemble branches. Then, using these components, an upside-down tree is constructed, complete with a center node, additional nodes, and leaf nodes. The technique is non-parametric and can handle huge, complex datasets with less need for a difficult parametric structure. The data from the study can be divided into a training dataset and a validation dataset once the sample size is large enough. A decision tree model can be created with the assistance of the training dataset. To create the best final model feasible, the validation dataset can be utilized to determine the ideal tree size.[13].

Although machine learning techniques are widely employed in many scientific fields, their application in the literature of the medical field is still limited, in part due to technical difficulties. K-nearest Neighbours, or kNN for short, is a simple machine learning technique. The paper begins with an explanation of the fundamental ideas at the core of the kNN algorithm before delving deeply into the details of kNN modeling in R. The required preparations for the dataset must be made before using R's on ()

function. The diagnostic precision of the model should be assessed after the result prediction using the kNN algorithm. The most common statistic to represent the kNN method is the one called ”average accuracy”. The k value, the distance calculation, and the choice of suitable predictors are a few elements that have a substantial impact on the model’s effectiveness. [14] (see Figure 1.6).

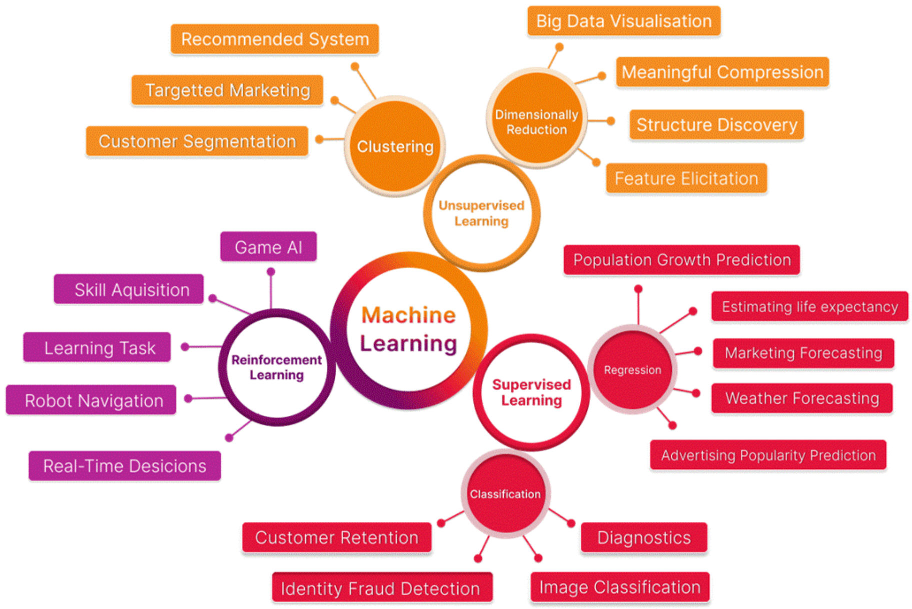


FIGURE 1.6: *Techniques of machine learning.*

A collection of weights is used to integrate the joint features produced from a set of features by encoding in a maximum entropy (ME) classifier, sometimes referred to as a conditional exponential classifier. An exponential conditional classifier is another name for this kind of classifier. Through encoding, each feature set and label combination is transformed into a vector. ME classifiers are a subset of the classifiers known as exponential or log-linear classifiers collectively. This is because I classifiers work by first extracting a collection of features from the input, then linearly combining those features, and then using the linear sum as the exponent. Point-wise mutual information (PMI) is the instrument that is used to discover the positive and negative words that are connected with the occurrence of a certain word when this technique is conducted in an unsupervised manner. The ME Classifier is one of the models that does not assume the presence of independent attributes. [15].

One of the most significant features of artificial intelligence is machine learning. Practically everywhere in the fields of science and technology may be found its uses. One of these industries is healthcare, where the application of machine learning has produced outstanding outcomes. Additionally, the use of machine learning in conjunction with the Internet of Things (IoT) has proven very successful in the healthcare sector. Nevertheless, this constantly developing technology hasn't yet made its way into all fields. Mental illness is one of the conditions for which a perfect cure has not yet been developed. Determining if a person has a mental condition in the first place is the challenging aspect. Meetings between a client and a psychologist in person, one-on-one, are necessary for the diagnostic and therapy processes. There is still some space for interpretation regarding the treatment. Although psychologists frequently recommend different medications to their patients, such as antidepressants, sleeping aids, and others, the prescription has not proved effective in treating or eradicating the disorder. A person may be experiencing a particular situation for a variety of reasons, including social pressures, professional responsibilities, family expectations, etc. Our inquiry into this matter will be limited to predicting such illness in the human body and figuring out what the person is experiencing by using data that has been previously recorded. We will use logistic regression, support vector machine (SVM), decision tree, K-nearest neighbor, and Naive-Bayes methods to build ensemble models and further analyze them. [16].

The most common psychological and mental ailment in our society today is depression. A sizable section of the world's population, including both young people and adults in contemporary culture, is afflicted by depression. A depressed individual may experience serious consequences if effective counseling is not provided or the condition is not identified early. By identifying depression early on, these consequences can be prevented. It is one of the main causes for which suicidal situations are made public. To assess whether a person is sad or not, this study tested six different machine learning classifiers utilizing a variety of sociodemographic and psychiatric data.[17].

A common yet serious mental health condition that many people experience is depression. Despite this, the majority of people who experience depression do not seek treatment for their illness. As a result, we have discovered that the content that is readily available to such persons makes it easier to analyze their mental problems. Applying several machine learning approaches, it is possible to extract a user's mental health state, with a focus on depression, from the data of social media sites. One of the greatest approaches to detecting sadness is to look for negative messages in the data that show negative because it is so common. To find potential answers to the problem, this study has examined a variety of machine learning techniques that may be applied to identify depression as well as the subject of detecting depression on social media. The ensemble learning approach is successful in locating a solution to this problem. Finding and using the approach and plan that will help us solve this problem the best is our goal. [18].

The identification of mental sickness itself is turning into a serious worry as a result of the much-increasing awareness of the need to maintain good mental health. Numerous psychiatrists have said that due to the complexity of each mental illness, it may be challenging to determine whether a patient has a mental condition. Due to this, it is challenging to provide a patient with the necessary care promptly before it is too late. Social media, however, has ingrained itself into people's daily lives, creating a scenario that can reveal more details about the patient's mental disorder. This study employed a systematic literature review (SLR), a technique for locating, assessing, and interpreting the many resources at one's disposal to offer solutions to a variety of research topics. The findings of an analysis conducted to address concerns about a text-based mental disorder detection system based on the social media activity of people with mental illnesses reveal that it is possible to diagnose depression earlier in society due to the presence of specific characteristics in how these subjects use their social media accounts. This SLR found that the bulk of studies on the early identification of depression cases use deep learning techniques like RNN because of the limited amount of data available. This was true even though just a small amount of research was conducted using a text-based technique. But this study's goal is to find potential strategies that might increase success [19].

People of various ages, genders, and races experience depression, which is a serious issue. Regardless matter where they reside, this is true. Because we live in a time of digital communication and technology, people are more at ease when it comes to sharing their ideas on social networking sites (SNS) almost daily. The objective of this work is to put out a model for diagnosing depression in anyone using data analytics. Under the notion that has been offered, the postings that users make on Twitter and Facebook, two of the most well-known social networking platforms, are mined for data. Based on the social media posts that a user makes, it has been concluded that he is depressed. The gold standard for diagnosing depression symptoms in a person is often a fully or semi-structured interview procedure (SDI). These procedures demand that the person provide a lot of information. On increasingly popular microblogging websites like Twitter and Facebook, people are expressing their opinions and engaging in more activities.

The analysis of the user's tweets and posts demonstrates the formation of depressive illness symptoms in the person. In this study, data gathered from users of social networking sites was evaluated using machine learning. It may be more efficient and accurate to categorize natural language processing (NLP) and diagnose depression using the Naive Bayes technique and Support Vector Machine (SVM).[20].

A kind of mental illness called depression affects more than 300 million individuals worldwide. In their daily lives, depressed people frequently battle worry. This can harm a person's relationships with their family and friends, lead to numerous illnesses, and, in the most extreme circumstances, culminate in suicide. The vast majority of people today convey their thoughts, feelings, and emotions on various kinds of social media as a result of the expansion of social networks. If a person's depression can be identified early by looking at their posts, the necessary steps can be taken to save them from depression-related illnesses or, in the best case scenario, from committing suicide [21].

Many people are still struggling with issues like anxiety, panic attacks, bereavement, sadness, and other psychotic disorders, even though the COVID-19 situation is beginning to improve in certain areas. Whether or not the person has firsthand experience with the sickness, this is true. Possessing the capacity to maintain mental fitness is one of the most significant traits somebody can acquire. People now have a place where they can openly express their thoughts and have conversations with others thanks to the advent of social networking sites [22].

The sentimental analysis procedure, a machine learning approach that helps in assessing a person's emotional state by analyzing the content of their online postings and extracting information from them, includes gathering useful information from such posts. Several machine learning algorithms are used on the dataset in this study, including gradient-boosted decision trees, gradient-boosted decision trees with adaptive boosting, bagged logistic regression, tree ensemble modeling, liblinear convolutional neural networks, and long short-term memory. The authors analyze the data using a variety of statistical measures, including accuracy, precision, recall, and the F1 score, and conclude that logistic bagging is successful. [23].

We are witnessing a radical change in how we live as a result of technological advancements like the Internet of Things and artificial intelligence, which are now permeating every aspect of our existence as humans. They have let us connect all of our gadgets and control them all with a single touch. Similar to this, anyone can easily share and express their thoughts on social media sites like Reddit, Telegram, Facebook, Instagram, Twitter, WhatsApp, and others, whether they take the form of lengthy messages, poetry, or photographs [24].

Everyone was forced to remain indoors due to the pandemic, where they could live out their daily routines in comfort. Communication, exchanging of thoughts, and points of view became even more crucial at this time. During these times of lockdown, the problem of depression grew more apparent, which also made the already challenging circumstances of people who suffer from mental health issues even more isolating. As a result, the field of depression detection has the potential to undergo a phenomenal transformation thanks to the early diagnosis of depression using data from social media platforms and the application of deep learning algorithms. This early detection strategy is especially pertinent given that most people communicate their feelings on social media platforms [25].

In the modern period, depression has become a common mental condition. Even though depression is considered a mental ailment, it may hurt a person's physical well-being. Most of the time, unless major physical or mental symptoms start to appear, people tend to ignore it. Examining what people are discussing or their conversations might be a helpful way to spot depression symptoms early on. This is a desirable alternative because it is significantly less invasive than other common medical testing while also having the potential to be quite accurate [26].

In the framework of this essay, we investigated this theory. To evaluate the text of the transcripts, we employed 10 different machine learning methods, including LSTM, SVM, ensemble techniques, random forests, and decision trees, among others. Data was acquired from voice messages. We applied the learning algorithms to the original transcripts of the chats to search for any patterns in the spoken language that people used to express despair. Among other noises, these patterns can be detected in screams, cheers, mumbles, whines, stutters, and murmurs. Our goal is to identify these patterns. [27].

The capacity for computers to "learn" independently and predict future occurrences without requiring human input is known as machine learning. Machine learning (ML) has a subset known as deep learning. It has been widely used in the medical field, where it is helpful for both patients and trained professionals. Clinicians in specialties including pathology, radiology, cancer, and radiology might benefit from seeing patient reports' photographs since it can help them spot trends in huge datasets and, as a result, make better treatment decisions [28].

According to the Globe Health Organisation, which estimates that there are 940 million people in the globe who are affected by mental health diseases, anxiety is the most common mental health problem, affecting 248 million people globally. Depression has a direct correlation to suicide. Mental illness is thought to be the cause of 8 million deaths annually or around 14.3 percent of all fatalities worldwide.

Whether they are long-term or short-term, if these signs of stress are recognized early on, it will stop a person from having suicidal thoughts. In a similar line, the medical industry also has access to a vast amount of data. Thanks to the usage of electronic health record (EHR) software, the process of digitizing people's personal health information, such as medical records, bills, and prescriptions, has started in several different countries. [29]

In modern society, psychological stress is a serious issue, especially for young people. The age group that was formerly considered to be the most carefree is now under a lot of pressure. Today's culture is experiencing higher levels of stress, which is the main contributor to several health problems, including depression, suicide, heart attacks, and strokes. In this particular piece of research, we will be assessing the level of mental stress that students encounter while surfing the internet a week before a test. [30]

Our objective is to look into the stress that college students encounter at various points in their lives. The effects of exam or job-related stress on students, frequently go unnoticed by the students themselves. We will investigate how these factors affect a student's mental health and link this stress to how much time is spent online. [31].

1.4 Depression detection using machine learning techniques

To provide the best alternative for identifying depression, a method has been presented that incorporates machine learning techniques. The survey was created with the aid of a psychiatrist for the objectives of this investigation. The comments were received from a variety of sources, including family, friends, and colleges and universities. The outcomes of applying the acquired dataset to previously created machine learning models are compared to those of the suggested model. To reduce the number of people who attempt or commit suicide in the future, the model that is being presented includes a tool for diagnosing depression with the use of machine learning techniques. [32].

1.5 Objectives

The objectives of the work are as follows:

1. To study and analyze existing sentimental analysis-based techniques.

2. To prepare the dataset from social media concerning COVID-19.

3. To Design and develop the system for identifying mental illness.

4. To evaluate the designed and proposed system with standard metrics.

1.6 Summary

Every aspect of depression in India during the COVID-19 period is covered in first chapter, including the causes of the high suicide rate. People in India commit suicide for a variety of reasons, including depression. Education, employment, obligations, the environment, and other factors are a few of them. The new coronavirus SARS-CoV-2 that produced the COVID-19 pandemic has had a significant impact on the world in a number of ways. These are a few of the main effects:Impacts on higher education, the economy, families, society, and mental health are among them. In the second chapter, we conducted a review of the pertinent literature, which resulted in the production of many unique concepts and the discovery of a market need for a questionnaire-based depression screening tool. The examination of methodology in the third chapter provides specifics on how we put the earlier principles into practice. The fourth chapter is devoted to going over the conclusions and judgements made.

CHAPTER 2

Literature Review

The idea of depression is broken down and investigated in this chapter. In this day and age, people are becoming increasingly depressed daily. The prevalence of depression has increased across all age groups as a result of a variety of variables working together. Depression is also classified according to its severity, with mild depression being the least severe, moderate depression being the next step up, and severe depression being the kind that can lead to death by suicide. This corpus of research goes thoroughly into the causes of the rise in the prevalence of depression across all age groups as well as the many machine learning techniques that may be applied to early depression detection.

2.1 Impact of depression

Every day, millions of individuals experience depression, yet very few of them receive the necessary support. In the past, doctors would personally speak with sad patients and utilize diagnostic standards established by licensed psychologists to determine what was wrong. A depressed individual is perpetually miserable, anxious, and hopeless. Additionally, they experience a variety of physical and mental health issues and lose interest in daily activities. One of the most significant societal problems that has grown more common in COVID-19 is depression. Even though many people are affected by this ailment, very few of them receive therapy. The second most prevalent mental health issue worldwide is depression. Suicide is a result of depression. The main reason why young people commit suicide is depression. Early diagnosis of a disease is crucial to halt its global spread and stop young people from committing suicide. There are several ways that depression can manifest. Early on in the disease, depression is typically treatable. On the other hand, a person with severe depression needs additional care and attention [33].

Numerous research have suggested that depression may be diagnosed using machine learning. Techniques for supervised and unsupervised learning are used to classify texts. Examples of supervised learning techniques include maximum entropy, neural networks, support vector machines, and Nave Bayes classification. Conversely, lexicon-based, dictionary-based, and corpus-based learning are unsupervised learning methods. [34].

Along with physical symptoms, a depressed individual frequently experiences feelings of sadness, helplessness, and loss of interest in routine activities. Doctors have examined depression in recent years by speaking with and treating patients one-on-one. However, a prior study found that the majority of patients did not get treatment when they were first depressed, which led to a worsening of their mental health. The insider claims that there is a lack of effort in the programs used to identify sadness on social media platforms like Twitter. An online application that does sentiment analysis and uses a classification feature to identify the percentage of depressed and non-depressive thoughts can overcome this problem. [35]. Supervised learning is becoming increasingly important as a result of the large number of electronic documents available from various sources. Because the process divides a bunch of documents into predefined groups based on their subjects, text categorization is established. Text classification's major goal is to extract information about textual resources. This research investigated data collection, text pre-processing, feature extraction, text classification, and other steps of text classification. Text classification was mostly done using supervised machine learning algorithms in various stages. According to the source, k-NN is effective in a variety of categorization strategies. [36].

A major mental health disease known as depression can have an impact on a person's emotional, cognitive, physical, and social well-being. The impact of depression can be severe, and it can affect every aspect of a person's life, including their ability to work, socialize, and take care of themselves.

2.2 Impact of depression during Covid-19

People all across the world have been affected by COVID-19. Along with the apparent physical symptoms in infected people, it has seriously harmed public mental health. Like other nations, India imposed a state of lockdown to stop the virus from spreading. The goal of the current study is to examine how the lockout has affected Indian residents' psychological health. A questionnaire including inquiries regarding depression, anxiety, stress, and family wealth was given to 43 participants. The study discovered that tension, anxiety, and melancholy are all negatively correlated with family income and that those who don't have the money to maintain the lockdown suffer the most. Studies have indicated that students and healthcare professionals have higher levels of stress, anxiety, and depression than people in other occupations. Regardless of the current situation, stress, anxiety, and depression levels in mental health practitioners were found to be within normal ranges, demonstrating their ability to remain normal in difficult circumstances. Mental health professionals could be able to help policymakers and other authorities deal with the psychological effects of COVID-19 [37].

The COVID-19 epidemic has had a significant impact on people's health and well-being throughout the world, and more and more people are becoming aware of how important it is to understand both the physical and psychological effects of COVID-19 experiences and stress. The current study used a convenience sample of

565 American individuals (57.9 percent male) recruited from MTURK to see how COVID-19-related stress affects anxiety, sorrow, and functional impairment.

The COVID-19 infection was connected to a higher likelihood of anxiety and depression diagnoses (ORs ¿ 3.0). Large percentages of the variation in anxiety, depression, health anxiety, and functional impairment were predicted by COVID-19-related stress in latent variable analyses (R2 = 30). These results suggest that COVID-19-related stress, friend deaths, and personal encounters with a COVID-19 diagnosis are all significantly associated with an increased risk of emotional disorder symptomatology and that the COVID-19 pandemic may increase the need for mental health care [38].

Public health is at risk due to the COVID-19 epidemic, which has affected every country on the earth since December 2019. The procedure will eventually affect the medical personnel addressing the epidemic. The study's objective is to evaluate the levels of stress, pessimism, and anxiety that Turkish healthcare workers encountered during the COVID-19 pandemic. An electronic survey was used to obtain the data. In the beginning, the Depression, Anxiety, and Stress Scale (DASS-21) was used. The second section of the poll made an effort to highlight the challenges healthcare professionals encountered throughout the outbreak as well as their workplace. The third section looked at the personnel's socio-demographic traits. A total of 2076 healthcare personnel contributed to the study. The primary source of worry or stress among healthcare professionals, according to the research, is the fear of infecting their families with the COVID-19 virus (86.9 percent). The study found that female workers have greater levels of dejection, anxiety, and tension than male workers ($p = 0.003$). Employees in the pandemic, emergency, and internal services have the greatest levels of depression, anxiety, and stress. P stands for probability. [39].

The goal of this study was to find out how common depression was in a community affected by COVID-19 and what factors were linked to it. The study was planned using a descriptive cross-sectional approach. Two weeks following Turkey's initial COVID-19 diagnosis, between March 23 and April 3, 2020, the research was conducted. Between the ages of 18 and 65, 1115 citizens of the Turkish Republic participated in the poll. The study was conducted utilizing online questionnaires and data was gathered using the Beck Depression Inventory and the Personal Information Form. Software from IBM SPSS Statistics, version 20, was used to analyze the data. Female participants between the ages of 18 and 29 who were single, enrolled in school, and whose income fell short of their needs scored more depressed than other participants. Lower levels of sadness were found in those who were worried about becoming sick and spreading it to others, who were overly clean, worried about the future, sorrowful, and uneasy. Participants who had to move during the quarantine reported feeling lonely, afraid of dying, helpless, having difficulties sleeping, feeling unworthy, starting to smoke and consume alcohol, and moderate melancholy. The levels of depression were lower among those who engaged in homeschooling, employment, or other activities, spent time with their families, or took time for themselves. [40].

Widespread issues with mental health have been brought on by the COVID-19 outbreak. As a result, during a pandemic, managing and monitoring the population's mental health comes first. To assess the prevalence of stress, anxiety, and depression in the general population during the COVID-19 pandemic, this study will review prior studies and make relevant findings.

Without regard to deadlines and up to May 2020, Science Direct, Embase, Scopus, PubMed, Web of Science (ISI), and Google Scholar were searched for articles on stress and anxiety in the general public during the COVID-19 pandemic. The random effects model was used to meta-analyze the data, and the I2 index was used to measure research heterogeneity. Moreover. The data was evaluated using the Comprehensive Meta-Analysis (CMA) program. [41].

It has become more apparent how broad the pandemic is since the first coronavirus disease 2019 (COVID-19) case was identified in Hong Kong three months ago. It is now necessary to consider the psychological effects of COVID-19. The current population-based study makes an effort to look at people's hopelessness and anxiety during the COVID-19 outbreak in Hong Kong. A structured questionnaire with sections for the PHQ-9, GAD-7, global rating of change scale, and COVID-19 was given to a group of people who were chosen at random. Of the 500 research participants, 19 percent (a PHQ-9 score of 10) and 14 percent (a GAD score of 10) reported having depression or anxiety. In addition, 25.4 percent of respondents reported that since the outbreak, their mental health has gotten worse. The lack of exposure to the 2003 SARS pandemic, fear of contracting COVID-19, lack of access to sufficient surgical masks, and inability to work from home were all linked to poor mental health, according to a multivariate logistic regression analysis. During the epidemic, residents should get psychological care, such as brief home-based psychological counseling. [42].

Because of the early lockdowns, the COVID-19 epidemic in Greece has taken a less dangerous path. However, the psychological effects of the lockdown are unknown. Furthermore, sickness beliefs and accompanying techniques to cope with the stress of the outbreak may have impacted adherence to the limitations. To ascertain the incidence of anxiety and sadness during the lockdown, the emotional effects of the epidemic, and the effects of coping mechanisms and sickness beliefs on mental health, we surveyed the Greek population. Adults were invited through social media during the lockdown's peak. The PHQ-9 and GAD-2 questionnaires were used to measure the symptoms of depression and anxiety, respectively. The Brief COPE questionnaire was used to measure coping abilities, while the updated Sickness Perception Questionnaire (IPQ-R) was used to assess disease beliefs. In total, 3379 people took part. The pandemic had a disproportionately negative impact on women and those who were struggling financially. Although they were consistent with prior tests, there were a lot of depression and anxiety symptoms. Participants demonstrated a high level of personal control and employed more constructive coping strategies to deal with the stress brought on by the pandemic. Younger students, those with higher emotional impact, those isolated due to symptoms, and those who were overexposed to media for COVID-19-related news were more likely to have depressive symptoms. Positive coping mechanisms and high degrees of personal and therapeutic control were connected to lower levels of depression. Increased depression symptoms during the lockdown were linked to specific psychological and social traits; this suggests that public health policies should be developed to lessen the epidemic's negative effects on mental health. [43].

The current COVID-19 (Coronavirus Infectious Disease 2019) outbreak has had a significant global impact. As a result of this terrible health crisis, millions of people have developed an upsurge in mental health conditions including despair, stress, worry, dread, disgust, melancholy, and anxiety, which has become one of the main public health problems. Along with hurting finances and society, depression can lead to major issues with emotions, behavior, and physical health. The user-generated content on Twitter is used in this study to examine the dynamics of community despair as a result of the COVID-19 epidemic. To create depression classification models, a novel method based on multimodal data from tweets and word frequency-inverse document frequency (TF-IDF) is proposed. Multimodal characteristics gather depression signs that are topical, affective, and domain-specific. We investigate the issue using recently obtained tweets from Twitter users in the Australian state of New South Wales. Our cutting-edge categorization technique can pinpoint events that take place during COVID-19 time and depressive polarity that may be affected by it. The findings show that after the COVID-19 pandemic, people's moods deteriorated. The state lockdown and other government initiatives contributed to the rise of depression [44].

To stop the disease from spreading, the Nigerian government has put strict quarantine rules in place all over the country. During the COVID-19 epidemic, both academic and non-academic staff at an African university, as well as their unemployed families, were tested for anxiety and depression. The research involved 69 individuals. There were 49 males and 20 females between the ages of 17 and 21 who took part in the study. The depression data was obtained using the Self-Reporting Questionnaire (SRQ-20), and the items were chosen based on prior and current pandemic research. Unemployed academic and non-academic personnel families had lower levels of anxiety and sadness than academic workers. Scores for anxiety and depression were shown to be related. A solid understanding of COVID-19 may result in academic professionals having low levels of anxiety and despair. Academic personnel reported a weak association between anxiety and depression, but non-academic and unemployed respondents had a strong link. According to the current study and literature, people's knowledge levels should be increased through Internet technologies to reduce anxiety and sadness. [45].

It has been hypothesized that the COVID-19 pandemic will be detrimental to mental health. Governments all around the world have implemented a variety of public health measures to stop the spread of Sars-CoV-2, ranging from suggestions for physical isolation to directives to stay at home, all of which have had a disastrous impact on people's daily lives. However, there is currently a dearth of research connecting the COVID-19 epidemic and public health initiatives to mental health. This study (N = 4335) looked at the effects of sociodemographic and COVID-19-related factors on acute mental health outcomes in a state-wide population sample of adults in Germany. On anxiety and depression symptomatology, health anxiety, loneliness, the frequency of scared episodes, psychosocial distress, and life satisfaction, the effects of various types and levels of restriction imposed by public health measures (such as quarantine, and stay-at-home orders) were examined. Higher mental health impairments were linked to lockdown procedures, a decline in social ties, and a stronger sense of life changes. Importantly, a purported stay-at-home order was connected to poor mental health despite being informally and widely publicized. In these trying times, especially for vulnerable populations, proper risk communication and specialized mental health guidelines are essential [46].

Numerous people are experiencing tremendous stress, worry, and depression as a result of the COVID-19 pandemic's unanticipated obstacles and disruptions to our way of life. People who suffer from depression have feelings of sadness, hopelessness, and disinterest in or joy over routine activities. Following are a few effects of depression during COVID-19:

- **Increased prevalence of depression:**

Studies have shown that the COVID-19 pandemic has led to an increase in the prevalence of depression worldwide. The fear of getting infected, social isolation, financial strain, and uncertainty about the future are some of the reasons behind this increase.

- **Worsening of pre-existing depression:**

  People with pre-existing depression may experience worsening of their symptoms due to the pandemic. The disruption of daily routines, reduced access to mental health services, and social isolation can all contribute to the worsening of depression symptoms.

- **Increased risk of suicide:**

  The pandemic has also increased the risk of suicide. Depression is a major risk factor for suicide, and the stress, uncertainty, and isolation caused by the pandemic can exacerbate this risk.

- **Impact on physical health:**

  Depression can have significant impacts on physical health, including a weakened immune system, increased inflammation, and increased risk of chronic diseases. These impacts can further exacerbate the negative health consequences of COVID-19.

- **Impact on relationships:**

  Depression can also impact relationships, including romantic relationships, family relationships, and friendships. The stress and isolation caused by the pandemic can lead to increased conflict, communication difficulties, and feelings of loneliness and disconnection.

- **Impact on work and productivity:**

Depression can also impact work and productivity. People with depression may struggle to concentrate, complete tasks, and meet deadlines. This can lead to decreased job performance, increased stress, and potential job loss.

- **Increased healthcare costs:**

  The increased prevalence of depression during the pandemic can also lead to increased healthcare costs. People with depression may require more frequent medical visits, prescription medications, and mental health services.

Overall, the COVID-19 pandemic has had a significant impact on mental health, including an increase in depression. It is important to seek help if you or someone you know is experiencing depression symptoms. Mental health services are available, including telehealth options, to help manage and treat depression during this challenging time.

Increased prevalence of depression

The COVID-19 pandemic has caused unprecedented levels of stress and uncertainty, leading to an increase in the prevalence of depression worldwide. Here are some of the factors that contribute to the increased prevalence of depression during the pandemic:

- **Fear of getting infected:**

  The fear of contracting COVID-19 can cause significant stress and anxiety, especially for those who are considered high-risk due to underlying health conditions or age. This fear can lead to feelings of hopelessness and despair, which are common symptoms of depression.

- **Social isolation:**

  The pandemic has also led to social isolation due to lockdowns, social distancing, and quarantine measures. This isolation can lead to feelings of loneliness, sadness, and disconnection, which are all symptoms of depression.

- **Financial strain:**

  The economic impact of the pandemic has caused financial strain for many people, including job loss, reduced income, and increased debt. Financial strain can lead to feelings of hopelessness, despair, and anxiety, which are all common symptoms of depression.

- **Disruption of daily routines:**

  The pandemic has disrupted daily routines, including work schedules, school schedules, and leisure activities. The lack of structure and routine can lead to feelings of disorientation, anxiety, and depression.

- **Uncertainty about the future:**

  The pandemic has also created a sense of uncertainty about the future, including concerns about the long-term impact of the virus, economic stability, and personal health. This uncertainty can lead to feelings of anxiety and depression.

- **Reduced access to mental health services:**

  The pandemic has also led to a reduction in access to mental health services, including in-person therapy and counseling. This lack of access can make it difficult for people with depression to get the help they need to manage their symptoms.

Worsening of pre-existing depression

People with pre-existing depression may experience worsening of their symptoms during the COVID-19 pandemic due to a variety of factors. Here are some of the reasons why pre-existing depression may worsen during the pandemic:

- **Disruption of routine:**

  The pandemic has disrupted daily routines, including work schedules, school schedules, and leisure activities. This lack of structure and routine can lead to feelings of disorientation, anxiety, and depression, which can exacerbate pre-existing depression symptoms.

- **Social isolation:**

  The pandemic has also led to social isolation due to lockdowns, social distancing, and quarantine measures. This isolation can lead to feelings of loneliness, sadness, and disconnection, which can exacerbate pre-existing depression symptoms.

- **Increased stress and anxiety:**

  The pandemic has caused significant stress and anxiety for many people, including concerns about personal health, job security, and financial stability. This increased stress and anxiety can exacerbate pre-existing depression symptoms.

- **Reduced access to mental health services:**

  The pandemic has also led to a reduction in access to mental health services, including in-person therapy and counseling. This lack of access can make it difficult for people with pre-existing depression to get the help they need to manage their symptoms.

- **Fear of getting infected:**

  People with pre-existing depression may be more vulnerable to the fear of getting infected due to their already heightened sense of anxiety and worry. This fear can exacerbate pre-existing depression symptoms and make it difficult to manage.

Increased risk of suicide

The COVID-19 pandemic has brought about significant challenges and stresses that can increase the risk of suicide. Here are some reasons why the pandemic may increase the risk of suicide:

- **Isolation and loneliness:**

Social isolation, quarantine measures, and physical distancing protocols can leave people feeling isolated and disconnected from others. This can lead to feelings of loneliness and hopelessness, which are known risk factors for suicide.

- **Economic hardship:**

  The pandemic has led to widespread job loss, financial strain, and economic hardship, which can increase stress and anxiety levels. These financial struggles may contribute to the development or worsening of depression, which is a major risk factor for suicide.

- **Increased stress and anxiety:**

  The pandemic has caused significant stress and anxiety for many people, including worries about personal health, job security, and financial stability. These increased stress levels can exacerbate mental health conditions and contribute to suicidal thoughts.

- **Disruption of mental health services:**

  The pandemic has disrupted access to mental health services, including in-person therapy and counseling. This lack of access can make it difficult for people to receive the support and treatment they need to manage their mental health.

- **Fear and uncertainty:**

  The pandemic has caused significant fear and uncertainty about the future, including concerns about the long-term impact of the virus, economic stability, and personal health. This uncertainty can contribute to feelings of hopelessness and despair, which are also known risk factors for suicide.

Impact on physical health

The COVID-19 pandemic has had significant impacts on physical health, both directly and indirectly. Here are some of the ways that COVID-19 has impacted physical health:

- **Direct impact on health:**

  COVID-19 is a respiratory illness that can cause serious health complications, including pneumonia, acute respiratory distress syndrome (ARDS), and death. The virus primarily spreads through respiratory droplets when an infected person coughs, sneezes, or talks. Those with underlying health conditions, such as heart disease, diabetes, and obesity, are at greater risk of experiencing severe symptoms and complications.

- **Delayed medical care:**

  The pandemic has caused a significant strain on healthcare systems, leading to delayed or canceled medical care for non-COVID-19 health conditions. Delayed medical care may lead to worsened health outcomes for conditions such as heart disease, cancer, and mental health conditions.

- **Disruption of routine healthcare services:**

  Many routine healthcare services, such as check-ups, preventive screenings, and vaccinations, have been disrupted or delayed during the pandemic. This disruption may lead to missed diagnoses and health conditions going untreated.

- **Increased stress and anxiety:**

  The pandemic has caused significant stress and anxiety for many people, which can contribute to a range of physical health conditions. Stress can lead to increased blood pressure, heart rate, and cortisol levels, all of which can have negative impacts on physical health.

- **Lifestyle changes:**

  The pandemic has led to significant changes in lifestyle, including reduced physical activity, changes in diet, and increased alcohol and substance use. These lifestyle changes may contribute to the development or worsening of chronic health conditions.

Impact on relationships

The COVID-19 pandemic has had significant impacts on relationships, both positive and negative. Here are some of the ways that COVID-19 has impacted relationships:

- **Increased time spent with family members:**

  Stay-at-home orders and remote work have led to increased time spent with family members, including partners, children, and extended family. For some, this has strengthened relationships and created opportunities for bonding.

- **Strained relationships:**

  The pandemic has caused significant stress and uncertainty, which can lead to strained relationships. Financial stress, concerns about health, and limited social interactions can all contribute to increased tension and conflict in relationships.

- **Changes in communication:**

  The pandemic has led to changes in communication, including increased use of technology to stay in touch with loved ones. Some people may struggle with these changes, while others may find new and creative ways to connect with others.

- **Reduced social support:**

  Social distancing and quarantine measures have led to reduced social support, which can contribute to feelings of loneliness and isolation. This can be particularly challenging for those who live alone or who are isolated from their usual support systems.

- **Relationship challenges for front-line workers:**

  Front-line workers, including healthcare workers and first responders, may experience relationship challenges due to the increased stress and demands of their jobs. These challenges may include difficulty balancing work and personal life, increased risk of exposure to the virus, and concerns about spreading the virus to loved ones.

Impact on work and productivity

The COVID-19 pandemic has had significant impacts on work and productivity, both for individuals and for businesses. Here are some of the ways that COVID-19 has impacted work and productivity:

- **Remote work:**

  Many businesses have transitioned to remote work to comply with social distancing guidelines and prevent the spread of the virus. While remote work can provide flexibility and reduced commuting time, it can also create challenges such as a lack of social interaction and difficulty separating work and personal life.

- **Job loss:**

  The pandemic has caused significant economic disruption, leading to job losses and reduced income for many individuals. This can lead to financial stress, anxiety, and uncertainty about the future.

- **Increased workload for front-line workers:**

  Front-line workers, including healthcare workers, essential workers, and first responders, have experienced increased workloads and high levels of stress during the pandemic. This can lead to burnout and decreased productivity.

- **Disruption to supply chains and business operations:**

  The pandemic has disrupted supply chains and business operations, leading to decreased productivity and increased costs for many businesses.

- **Changes in demand for goods and services:**

Changes in consumer behavior and decreased economic activity have led to changes in demand for goods and services. This can create challenges for businesses and workers who rely on specific industries or products.

Increased healthcare costs

The COVID-19 pandemic has led to increased healthcare costs in several ways:

- **Increased demand for healthcare services:**

  The pandemic has led to increased demand for healthcare services, including hospitalizations, testing, and treatment for COVID-19. This increased demand can lead to higher healthcare costs, both for individuals and for insurance providers.

- **Increased use of personal protective equipment (PPE):**

  Healthcare workers require PPE to protect themselves and others from the spread of COVID-19. The increased use of PPE can lead to increased healthcare costs for hospitals and healthcare providers.

- **Development of new treatments and vaccines:**

  The development of new treatments and vaccines for COVID-19 requires significant investment in research and development. These costs are often passed on to patients and insurance providers.

- **Disruption to healthcare services:**

  The pandemic has led to disruptions in healthcare services, including delays in routine medical care and elective procedures. This can lead to higher healthcare costs in the long term, as untreated or delayed conditions may require more intensive and costly treatment in the future.

- **Increased use of telemedicine:**

  To reduce the risk of transmission of COVID-19, many healthcare providers have increased their use of telemedicine to provide remote consultations and treatment. While telemedicine can be more convenient and cost-effective in some cases, it can also require additional equipment and training for healthcare providers.

2.3 Review analysis of machine learning techniques for detecting depression

Social networking is another type of medical help that can be used to look for signs of mental illnesses like depression. In this article, a summary of the findings of an analysis employing methodologies and techniques of emotion analysis is provided. The study aimed to identify depressive mood disorders. The author focused most of their attention on studies that can automatically recognize unusual patterns of behavior on social networks. Classic off-the-shelf classifiers were used in the research to evaluate the information that is now available for use in lexicons [47]. The number of people making payments via digital methods has skyrocketed in Indonesia during the past several years. There are a wide variety of pricing options available for this digital service from many different companies. The majority of individuals express their thoughts and emotions to one another via social media platforms like Twitter. To apply machine learning to data gleaned from Twitter, this study applies the Naive Bayes classifier and the K-Nearest Neighbour method. The study's conclusions show that customers think highly of LinkAja and Go-Pay in comparison to other service providers [48].

Clarification has been provided on the connection between people's stock comments and social media platforms. Pantip.com is the name of the Thai stock market. There is a tool for tagging available on this website. This website uses the category "Stock" for all of its entries. This model has a 74 percent accuracy rate. According to the findings of this investigation, the stock quantities of ADVANC and CPALL are a contributing factor to the sentiments expressed on social media. [49].

Mining opinions in Persian is a pioneering topic of research that should be recognized for its accomplishments. The study of the Persian language may be broken down into two categories: those that emphasize lexicons and machine learning. To overcome polarity, several strategies are utilized. This study takes a methodical approach to machine learning and lexicon-based approaches, and it then suggests a hybrid strategy as a fix for the issue of rating prediction in Persian [50]. Customer Experience Management is a strategy that is used to enhance and improve customer service. In this study, we use sentiment analysis to assess customer experiences based on comments from consumers. Because there is a great amount of unstructured data available on social media sites, it is necessary to use the Naive Bayes classification classifier to contribute to the sentiment analysis process [51]. The fast growth of social media has made it simple for the general population to express their opinions, which makes it possible to better monitor the spread of illness across a variety of geographic areas. People can share their ideas and viewpoints on a variety of topics via Twitter, which is one of the most popular social networks. The author gave health advice. Twitter analysis uses sentiment analysis to look at tweets on health. The author reveals the discrepancy between the job that is now being done and how it is being presented, both in terms of accuracy. The recommended method is an original way to categorize health traits for depression and helps to determine a person's current health status in their home [52].

The writer recommended a brand-new program that should be named Bag of Sub-Emotions (BoSE). A lexical tool consisting of emotions and subwords is built into Fast-Text and used by the new representation to automatically construct close-grained emotions. These emotions are generated by the new representation. It generates performance that is superior to what was suggested by the baselines [53]. According to the findings of several studies, cyberbullying is responsible for 29 percent of the instances of sexual harassment that began on social networking sites. In addition to that, the study incorporated an examination of the market as well as the sentiment on Twitter. The analysis of user sentiment data was the method that was utilized to carry out this investigation. In addition, three objectives for usage in sentiment analysis have been outlined here: the identification of polarity, the identification of subjectivity and objectivity, and the study of characteristics and aspects. The method as a whole works toward the goal of describing the contextual polarity of an individual's online interactions, and it also contributes to the segmentation of the user's most frequently used terms.[54].

The author has created an emoji expression identification system. This system can identify a variety of emotions, including smiling, angry, crazy, hilarious, ill, drowsy, cool, and melancholy, among others. It then uses the KNN method to recognize the emoji once it has been extracted from the feature it was found in. The work consisted of categorizing images, and we found that employing emojis helped us get favorable results in the domain of emotions [55]. The author of this study suggests a method for visual sentiment analysis that combines both global and local specifics in its structure. If a particular picture does not contain any items that meet the criteria, no local information will be utilized; in this case, sub-images will be gathered based on the important object detection window [56]. At this point, the Internet is a vast ocean of raw data; yet, raw data can only be understood as information after being processed, established, and organized. To provide a solution to this issue of accurately assessing sentiments, a unique approach known as "partial textual entailment" was developed. It was used to examine the semantic similarity of tweets that were shared to make it simpler to group tweets that were linked to one another. The researcher claims that this method was initially implemented in this study to lessen the burden that is placed on the computer. [57].

It uses linear support vector machines and looks into which sources of information contribute the most to the goal of coming up with a complete list of characteristics. The goal of this work is to look into how cyberbullying-related posts on social media sites can be found automatically. The primary contribution of this research is the development of a method that can automatically recognize warning indications of cyberbullying on various social media platforms [58]. This Twitter study, in which the author analyzed the perspectives, feelings, expectations, and actions of individuals on an outdoor game called "Lawn Tennis," is where the research is being done at the moment. An investigation was conducted to determine the number of individuals who genuinely like playing this game as well as the game's level of popularity in a variety of regions. Hadoop was chosen due to its scattered design and ease of handling, both of which were important considerations given the massive volume of data that needed to be processed. [59].

The patient is depressed because depression shows up in their speech, facial expressions, and hearing. The author came up with the idea of combining many modes of communication, such as audio, video, and text, into one concept called the multi-modality mix to identify biomarkers that are predictive of depression. In addition to traditional medical tests, these so-called biomarkers, which can be audio, video, or written information, can be used to diagnose depression. As a result of this research, it is now clear that gender inequality, both in terms of verbal and nonverbal cues, has a big impact on how depression is diagnosed. [60].

The author has described a medical data science system that works by measuring a variety of emotions and using different ways to process those emotions. The design of this study was considered concerning the medical data belonging to patients within the context of data mining, data analytics, and data visualization. The main goal of this project was to develop a self-serving psychometric analyzer that can do rapid computational linguistics and provide a mental health summary based on previous research, patient medications, and therapy [61]. The apps that may be employed in social media difficulties with sentiment analysis have been introduced. The feelings that are conveyed through social media are a reflection of the general population. These public orientations reveal the genuine feelings that people have regarding their role in the catastrophe. Predicting the outcome of an election, analyzing the stock market, and providing individualized recommendations are three one-of-a-kind applications that demonstrate the significance of social media sentiment research. [62].

In this piece of research, the author presented a system that makes use of tweets as a database. It uses SentiStrength sentiment analysis to generate the training dataset and back-propagation neural networks to categorize the provided tweets as depressed or not depressed. With the assistance of this hybrid model, it is simple to determine the social activity, thoughts, and mental state of the patient who is suffering from depression [63]. In this particular piece of research, the author made use of the techniques of machine learning and statistical analysis to differentiate between the sad post and the non-depressive post. The approach that has been presented provides a further determination of the level of difficulty associated with each depressing item. The author assigned codes to each of the publications based on the key characteristics, techniques of data collection, pre-processing, and feature extraction, among other criteria. The purpose of this paper is to provide a review of the current state of the art in the field of research about machine learning methods [64]. In this study, the use of natural language processing on Twitter served as the primary emphasis for the demonstration of depression-oriented emotional analysis. Text-dependent AI for emotions is used to analyze Twitter data to spot signs of depression. The support vector machine and the naive Bayes classifier were both used in the class computation process. [65].

Researchers have shown more than once that user-generated content can be used to figure out how smart someone is. Since this is the case, it is easy to get all of the information about a person's attitude and pessimism from the user overview in SNS. The author of this study offered a novel approach to classifying users that make use of social networking sites (SNS) as a data source and artificial intelligence (AI) implemented in the form of a selection tool [66]. The author is responsible for the generation of the model; to arrange the UGC, he makes use of two distinct classifiers, namely, Support Vector Machine and Naive Bayes Support. At the end of the day, it assigns patients to one of the following four levels of depression severity: minimal, mild, severe, or extreme. The output was prepared for the three findings, including the sentiment analysis, the results of the SVM, and the outcomes of the Naive Bayes algorithm [67]. The purpose of a feelings investigation is to recognize ideas or sentiments. The methodologies behind sensitivity analysis might give helpful tools and frameworks for tracking mental illnesses like depression. In this work, we cover the uses of sentiment analysis as well as effective approaches for measuring and detecting depression [68]. With the use of social media, it is easy to determine whether or not a person is depressed based on the statements they post. The goal of this article is to investigate the extent to which an individual suffers from depression using cognitive philosophies, machine learning techniques, and natural language processing methods to derive emotions from written text. The author of this work has written this article. The author recognized the voting model and feature selection technique, and the work demonstrates that SVM is larger than both Naive Bayes and Maximum Entropy classifiers. Furthermore, the author distinguished between SVM, NB, and ME classifiers on sentence-level sentiment analysis for the depression aspect [69]. Twitter users who are sad are uncovered via the use of screening surveys and the users' tweets. To identify users who are suffering from depression, automated detection approaches are utilized. According to the findings of the study, symptoms of mental illnesses, including sadness and others, may be recognized in a variety of online settings. The processing of natural languages and approaches for machine learning have greatly benefited from technological improvements in recent years. [70].

The author of this study uses four cutting-edge machine learning classifiers—Naive Bayes, J48, BFTree, and OneR—to get the most accurate results possible for sentiment analysis. The experiments are carried out with the assistance of three datasets that have been painstakingly put together by hand. Two of the datasets come from Amazon, while the third comes from IMDB movie reviews [71]. The amount of effort that is put into diagnosing depression through the use of tools. In this work, a system is developed that is used to track tweets from users on Twitter and also to deliver updates when a disturbed individual is detected. The approach is presented and discussed in detail in the following sections. In addition, this method provides social workers with the opportunity to reach troubled individuals who need care in the early phases of their crisis [72]. Sentiment analysis is a subfield of Natural Language Processing (NLP) that attempts to characterize textual subjectivity and assists in the extraction and classification of people's ideas, opinions, perceptions, judgments, evaluations, and emotions about services. Exploration is being done in a variety of disciplines, including sociology, politics, and marketing, with the assistance of this method.[73].

Emotional analysis is a way of representing things automatically by looking at what other people think about certain goods, services, or experiences. Because of the large number of viewpoints being investigated, the practice is commonly referred to as opinion mining. The purpose of sentiment analysis is to develop an algorithm that is capable of identifying and classifying a range of different feelings and attitudes [74]. The most advanced form of human communication now available is social networking. Because of the widespread adoption of social networking, it is clear that one-on-one engagement is increasingly being shunned by the vast majority of individuals. The fact that social networking sites have their own culture, which disperses the personal contact of individuals, groups, and societies around the globe, is the primary reason why people prefer using social networking sites to interact with other people in person. In addition, the hybridization method has been implemented in sentiment analysis to improve the accuracy of categorization. The classification strategy based on machine learning achieves an accuracy of ninety percent when applied to the task of sorting tweets into positive, negative, and neutral categories [75]. The polarization of the signals in this work is identified by the internal model, which decreases the requirement for normalization since it eliminates the polarization. The effectiveness of the algorithm is improved by the use of this internal model. Along with the outcomes, the algorithmic technique also highlights the application's efficient operation, and this strategy helps avert suicide attempts brought on by cyber-depression [76].

The writer of this piece came up with a way to divide depressed people into two groups: those who show their symptoms and those who don't. When treating a serious depressive illness (MDD) one person at a time, the more complicated method is used. This developed strategy used Facebook as a reliable source to identify individual depression tendencies. Recent research suggests that using social media can help identify depression. This is probably because so many people express their emotions, ideas, and worldviews on social media. The author has researched spatial patterns to use GIS techniques to the data gathered from social media platforms to provide fresh perspectives for public health research. The purpose of the application is to categorize Twitter users who are in distress and to assess spatial designs with the use of GIS technology. This strategy has the potential to make the treatment options for depression more effective [77]. Several different classifiers may be used in machine learning, lexicon-based technologies, and hybrid technologies. It is essential for the person doing the classifying to have the ability to quantify the risk that is connected to each categorization choice. The Bayesian decision theory is an example of a mathematical approach to pattern recognition. The primary objective is to analyze and contrast the various approaches to categorization. The key objective is to explain why certain NB classifiers perform better than others and to what degree the optimal answer is different from the usual decision-making approach. According to the author, this novel geometrical understanding of the decision function would offer a fresh viewpoint on the research of probabilistic binary classifiers [78]. According to the author's description, data analysis in the psychology field was performed to identify users of social web apps who were dissatisfied. According to the author, emotion analysis is provided first and foremost to apply terminology and man-made standards to the evaluation of depression. The next step is to develop a model for the detection of depression that is based on the anticipated process; however, this depression model was constructed using Chinese terminology. Hemophilia was also discovered to be present in the user population of depression, which suggests that the friends of a depressed person are more likely to be suicidal and that various sorts of contacts have varied results. [79].

The Naive Bayes classifier is a widely used classification technique. This classifier is straightforward to identify, and classifiers are much easier to use. The intended form is then used to build a depression detection model; however, this depression model is based on Chinese terminology. Hemophilia was also discovered in the depression user community, implying that the depressed person's friends are more likely to be suicidal and that different forms of relationships have varying effects. The experimental findings have proven the efficacy of this algorithm when compared to other algorithms such as CART, DT, and MLP's [80]. As cases of the 2019 coronavirus disease (COVID-19) grew, panic buying was observed all across the world, indicating that the sickness had more of an impact on mental health than it did on physical health. It is not understood how the epidemic has affected psychological impacts, stress, anxiety, and depression. This longitudinal study twice polled the general populace during the first outbreak and the peak epidemic four weeks later to gather demographics, symptoms, awareness, concerns, and COVID-19 prevention strategies [81]. To evaluate the levels of anxiety, stress, and depression experienced by physicians during the COVID-19 epidemic, as well as associated variables in both clinical and general settings. An online poll was conducted during the COVID-19 epidemic to investigate the psychological reactions of healthcare workers and related aspects. Three subsections address the following topics: 1) demographic information 2) information about the working conditions of persons 3) DAS-21 (Depression Anxiety and Stress Scale) (DAS-21). [82].

The objective of this study was to identify traits among young adults in the US during the COVID-19 era that were associated with symptoms of depression, anxiety, and PTSD. This cross-sectional online survey looked at 898 people from April 13, 2020, to May 19, 2020, about a month after the US proclaimed a state of emergency due to COVID-19 and before the initial easing of restrictions in 50 states. Asian Americans and Hispanics/Latinos had lower rates of severe mental health symptoms and severe anxiety, respectively, as compared to whites. Initial recommendations on the therapeutic management of mental health concerns connected to COVID-19 is one of these aspects [83]. The study of social networks will assist us in comprehending the intractable problems that are fundamental to the challenges of today's healthcare system: silo work, bottlenecks, discrepancies, inadequate coordination, professional alienation, and other social structures that are susceptible to undermining patient safety and quality care. In this study, we discuss the practical and ethical obstacles that healthcare researchers encounter when creating and collecting high-quality network data. To address these issues, the article provides practical advice [84].

When comparing our sample to the "gold standard" data sources, we use post-stratification weighting techniques to adjust for differences. We also address sample selection issues. Univariate and multivariate correlations are evaluated by comparing the shift data to the Current Population Survey and the National Longitudinal Youth Survey 1997. In our conclusion, we address several critical lingering shortcomings in the Facebook strategy and emphasize some of its important benefits, such as its cheap cost, capacity for swift data collection in response to research opportunities, and extensive and scalable sample targeting capabilities. We also offer some more applications for this technique.[85]. In this study, the most popular microblogging network, Twitter, is the main focus as a platform for sentiment analysis. We show how to gather a corpus automatically for sentiment analysis and opinion mining. We analyze the language and provide the phenomena the obtained corpus indicates. Using the dataset, we develop a sentiment classifier capable of evaluating a document's positive, negative, and neutral sentiments. The results of experimental evaluations demonstrate that our proposed strategies are effective and outperform those previously proposed. We used English in our investigation, but the method presented applies to any language. Increased chances for qualitative research are provided by advancements in communication technology. Zoom, an innovative video conferencing tool, has several features that might make it more appealing to qualitative and mixed-methods researchers. The advantages and disadvantages of using Zoom as a technique of data collecting are also not well known. We discuss the viability and acceptability of using Zoom to obtain qualitative interview data in the context of health research to better understand its application for qualitative and mixed-methods researchers [86]. Data collection in phenomenological research may be challenging, and the use of diaries is a sector of data collection that is frequently understudied. To help the reader comprehend how diaries might be used to collect data in phenomenological analysis, The author investigates how diaries might provide unvarnished insight into a phenomenon. Diaries can aid in the development of a personal comprehension of a phenomenon. [87]

This website is meant to help students who, as part of their academic work, conduct research courses, write a research proposal, or who are nascent researchers who are prepared to conduct interviews as a data-gathering strategy. Researchers must perfect their interviewing skills, choose the best approach, and rigorously prepare for every step of the process to conduct a successful interview. [88]. This study aimed to present novel qualitative research methodologies that may shed light on topics linked to psychiatric education, training, and patient care. Researchers and psychiatric practitioners have access to a variety of techniques for gathering data. These may be used independently or in conjunction with other quantitative and qualitative methods [89]. Data collecting is a significant barrier in machine learning and is still under investigation in several fields. There are two main reasons for the recent interest in data collecting. Second, we are seeing the introduction of new applications that require enough labeled data as machine learning becomes more pervasive. Second, deep learning algorithms build features automatically in contrast to standard machine learning, reducing functional engineering costs but needing more labeled data in return. We provide a study landscape of several tactics, provide instructions on when and how to use each tactic and pinpoint intriguing research issues. A lot of new research is made possible by the intersection of machine learning and data collection management, which is a bigger trend towards integrating Big Data and Artificial Intelligence (AI) [90]. On Twitter data, we do sentiment analysis. The contributions of this study are as follows: (1) We introduce previous polarity characteristics specific to the POS. We study the usage of a tree kernel to eliminate the requirement for repeated function engineering. The new features (together with previously recommended features) and the tree kernel operate at almost the same speed, and both surpass the state-of-the-art features [91]. In contrast to cooperative research, collaborative fisheries research focuses on academic collaboration between academics and fishermen and is an effective method for collecting stock assessment data and assessing marine protected areas. This effort has demonstrated that it may serve as a model for other sectors seeking to implement collaborative research and that collaborative research can greatly help to realize culture-centered co-management of marine resources. [92].

This systematic review aims to explain the findings of past studies that employed machine learning (ML) algorithms to scan text data from social media for indicators of depression and to make recommendations for future research in this area. Between January 1990 and December 2020, a bibliographic search was conducted in Google Scholar, PubMed, Medline, ERIC, PsycINFO, and BioMed. Two reviewers each found and looked at 17 of the 418 studies to see if they met the criteria for inclusion. Ten studies found depression based on what they thought the person's mental state was, five studies found depression based on what the person said about their mental health, and two studies found depression based on how involved the person was in the community. Thirteen of the seventeen studies used supervised learning techniques, three used unsupervised learning techniques, and one did not specify its ML technique. More study is required in areas like sampling, prediction algorithm optimization and characteristics, generalizability, privacy, and other ethical considerations [93].

Several studies have been conducted using machine learning algorithms to predict sorrow from social media user posts. Using social media data, the researcher may identify whether or not the users are sad. The technology of machine learning enables precise data categorization and the identification of depressed and non-depressive data. The proposed research study attempts to detect a user's depression using social media data. The Twitter data is then input into two distinct classifiers: Nave Bayes and NBTree, a hybrid model. We will identify the ideal method for detecting depression by comparing the results based on the greatest accuracy value. The findings demonstrate that both algorithms work similarly by demonstrating the same degree of precision. [94].

Increased reliance on technology may result in less physical activity. Constant stress may also raise the chance of developing a mental disease. Risks include peer pressure, heart attacks, depression, and a range of other issues. Different methods for predicting depression are investigated in detail in this study. In addition to surveys, social media posts, spoken communication language, and facial expressions are used to collect data. The result is generated from the extracted information. The intended outcome is that the individual will need care. To analyze the mental health status of a target population, this study compares several machine learning methods and classifiers, such as Decision Trees, SVM, Naive Bayes Classifier, Logistic Regression, and KNN Classifier. The intended audience for this identification approach is the general public, which includes working adults, college students, and pupils in high school. The study also shows how the Twint Twitter scraping tool may be used to determine whether a certain tweet is depressing [95].

In today's world, when the number of people using the internet and social media is growing at a rate that has never been seen before, Today's culture places a great deal of importance on the early detection or identification of emotional states. Psychiatric diseases are extremely hazardous, and they currently impact over 300 million people worldwide. This is the impetus for attempting to solve the research problem through innovative research publications. Early identification is essential for potentially lowering the number of persons who have this illness. This research study analyses a typical dataset obtained from social media sites, with detection potentially relying on a machine learning algorithm. [96].

The majority of people experience at least one of the mental health issues like stress, anxiety, or depression in today's contemporary culture. The use of machine learning algorithms allowed the authors of this article to make predictions regarding anxiety, depression, and stress. To put these algorithms into practice, data were gathered through the use of the Depression, Anxiety, and Stress Scale questionnaire from individuals who were employed and individuals who were jobless from a variety of cultures and communities (DASS 21). Five separate machine learning algorithms each predicted that anxiety, sadness, and stress were likely to occur at one of five different severity levels. These algorithms are especially well-suited to the task of predicting psychological disorders because of their high degree of accuracy. The confusion matrix's classes were found to be unbalanced when the various ways were put into use. The Random Forest classifier was found to have the greatest accuracy model out of the five algorithms used as a consequence of the inclusion of the f1 score parameter.

The algorithms were also shown to be particularly sensitive to unfavorable outcomes by the specificity parameter. [97].

Depression is a mental illness that has caused a lot of worry in our culture and has been of great interest to researchers all over the world for a long time. Even though a lot of research has been done on individual moods like depression, anxiety, and stress, with the help of activity logs from pervasive computing devices like smartphones, the question of how to predict depressed moods still hasn't been answered. In this article, we present a depression analysis and suicidal ideation detection system that we have suggested to predict suicidal behaviors based on the level of depression that a person is experiencing [98]. We were able to acquire real-time data from pupils as well as their parents by having them fill out questionnaires that were quite comparable to the PHQ-9 (Parent Health Questionnaire) These questionnaires included questions such as "What is your age?" or "Do you attend school or college consistently? and turned it into relevant data with attributes such as age, gender, and attendance history at the institution, among other things. After that, classification machine algorithms are used to train and categorize it into one of five phases of depression based on its severity: minimal or none, mild, moderate, fairly severe, and severe depression. In this particular dataset, utilizing the XGBoost classifier resulted in the highest possible accuracy, which was 83.87 percent. In addition, data was collected in the form of tweets, which were then categorized using classification algorithms according to whether or not the person who tweeted was experiencing depression. The Logistic Regression classifier achieved the highest level of precision, which was 86.45 percent for the same [99].

Depression is a frequent form of mental disease that can hurt performance as well as increase the risk of suicidal ideation and behaviour. Traditional methods that are utilized by professionals in the field of mental health can be of assistance in establishing the type of depression that an individual suffers from. Machine learning and natural language processing were used to gain an understanding of how to accurately predict posts that indicate depression in people. In the course of this research, we made use of a dataset obtained from Reddit. Because of its punctuality in the exchange of ideas, diversity in the presentation of emotions, and suitability to use medical jargon, Reddit is a perfect location to utilize as a supplement to the conventional public health system. Regarding thoughts of suicide, we looked over the postings and comments made by users [100]. We made use of natural language processing (NLP) to improve our comprehension of transdisciplinary topics that are associated with suicide. We came across two communities that provide support for those struggling with depression and suicidal thoughts: r/depression and r/SuicideWatch. People who are struggling with suicidal ideation frequently visit the popular "SuicideWatch" subreddit, which provides important warning signs for people engaging in suicidal conduct. After a quick skim through the articles, it is clear that the subreddits are genuine online communities where people can go to get help and share open and honest text data regarding the mental health of other people. Multiple machine learning methods, such as Naive Bayes and SVM, have been utilized in this work. [101].

Social media sites like Twitter, Facebook, Reddit, and Instagram, among others, have developed over the past few years into a forum where people can talk about their ideas and experiences. This offers the scientific community a fantastic opportunity to use such data in the early diagnosis of psychological diseases like "depression" (a mood disorder characterized by feelings of hopelessness and alienation). This study article's main objective is to assess how well various machine learning models perform on Twitter data that has been labeled, along with addressing the issue of class imbalance. In addition to a range of machine learning techniques, this study introduces several distinctive baseline feature engineering methods. Evaluation measures such as the f1-score, accuracy, and recall have been used to compare the efficacy of different models. This study effort uses the Bag of Words with AdaBoost Classifier, which delivers better results when compared to other machine learning classifiers [102].

Social networks have evolved into a potentially fruitful venue for individuals to contact friends who share their interests, as well as to share images, videos, and thoughts. Additionally, it has been a developing area of research and has recently established itself as a prominent position globally. Within the scope of this study, we investigated the prevalence of depression among various Facebook users. Already, a lot of academics have examined and applied a wide variety of methods to diagnose sadness; nevertheless, it is still necessary to detect it effectively using data collected from social networks. In light of this, we study the prospect of making use of data from Facebook and applying the KNN (k-nearest neighbors) classification algorithm to identify depressive feelings. We have reason to believe that the investigation and strategy we used will be useful in raising awareness among people who use online social networks. [103].

2.4 Review of existing techniques for detecting depression

Several tools and scales are commonly used for the detection of depression. Some of the most widely used tools are:

- **Beck Depression Inventory (BDI)**

  The Beck Depression Inventory (BDI) is a widely used questionnaire that people fill out on their own to find out how bad their depression symptoms are. Dr. Aaron T. Beck created the BDI in the 1960s, and since then, it has undergone several revisions. The questionnaire has 21 multiple-choice questions, each with four answers that range from 0 to 3 in terms of how serious they are. The questions cover a range of depression symptoms, including sadness, guilt, fatigue, appetite disturbance, and sleep disturbance. The total score is obtained by summing the scores for all 21 items, with a possible range of 0 to 63. The BDI is meant to find out if someone is depressed and how bad their symptoms are, but it is not a diagnostic tool. It can be used as a screening tool to find people who may be depressed and could benefit from seeing a mental health professional for more help.

With strong internal consistency and test-retest reliability, the BDI has been demonstrated to be a viable and accurate approach to evaluating depression symptoms. It has also been demonstrated to be sensitive to changes in the course of depressive symptoms. The BDI has been used to gauge the efficacy of various depression therapies, including psychotherapy and medication, in clinical and research contexts. Additionally, it is employed in depressive screening programs and epidemiological investigations.

However, it is important to note that the BDI should not be used in isolation to diagnose depression or to make treatment decisions. It is always important to seek a professional evaluation and treatment plan from a mental health professional [104]

- **EQ-5D**

  EQ-5D is a standardized health-related quality-of-life instrument used to measure an individual's health status. It was developed by the EuroQol Group, a non-profit organization consisting of a multidisciplinary group of researchers from various countries. The EQ-5D was first introduced in 1990 and has undergone several revisions since then. A self-reported questionnaire called the EQ-5D assesses five areas of health: mobility, self-care, regular activities, pain/discomfort, and anxiety/depression. There are three rating categories for each domain: no difficulties, minor problems, and major problems. On a range of 0 to 100, with 0 representing the worst possible health condition and 100 representing the best possible health state, people are asked to assess their overall health status using a visual analog scale (VAS). A health utility score is created using the answers to the EQ-5D questionnaire. This value goes from 0 to 1, with 0 denoting the poorest possible health state and 1 denoting the highest possible health condition. The EQ-5D is frequently used in clinical and health-economic assessments to evaluate the efficacy of interventions and therapies and to guide choices about how to allocate resources.

The EQ-5D is a flexible tool that can be used in clinical trials, population health surveys, and health technology assessments, among other places and groups. It has been translated into numerous languages and validated in many countries. It is also used in many countries as a tool for assessing health-related quality of life for population health surveys. One of the strengths of the EQ-5D is its brevity and ease of use, which makes it suitable for use in large population-based surveys. Another strength is its ability to generate a single summary score that can be used to compare health states across different populations and interventions. However, its simplicity may limit its sensitivity to detect changes in specific domains of health. Overall, the EQ-5D is a useful tool for assessing health-related quality of life and has been widely used in clinical and health economic evaluations. [105]

- **Hamilton Depression Rating Scale (HAM-D)**

  The Hamilton Depression Rating Scale (HAM-D) is a questionnaire that is often used by clinicians to measure how bad a person's depression symptoms are. It was developed by Max Hamilton in the 1960s and has since undergone several revisions. The HAM-D consists of 17 to 21 items, depending on the version used, each rated on a scale of 0 to 2 or 0 to 4, depending on the severity of the symptom. The items cover a range of depression symptoms, including mood, feelings of guilt, suicide ideation, sleep disturbances, and somatic symptoms. When you add up the scores for each item, you get the total score, which can be anywhere from 0 to 54 or 0 to 66, depending on which version you use.[106]

  The HAM-D is made to measure how bad a person's depression symptoms are, and it can also be used to track how symptoms change over time. It is frequently used in clinical trials and research studies to evaluate the effectiveness of various treatments for depression. The HAM-D is a valid and reliable way to evaluate depressive symptoms, with strong internal consistency and inter-rater reliability. However, there are several issues with its use. Firstly, it is a clinician-administered measure, which means that it is subject to clinician bias and may not reflect the individual's own experience of their symptoms. Secondly, it may not be sensitive to some aspects of depression, such as cognitive symptoms or anxiety. Despite these drawbacks, the HAM-D is nevertheless a commonly used indicator of the severity of depression in clinical and research contexts. It can be used to track changes in symptoms over time and offer useful information regarding the intensity of depressive symptoms. To offer a thorough assessment of a person's depression, it must always be used in concert with other measures and clinical examinations.[107]

- **Montgomery-Asberg Depression Rating Scale (MADRS)**

The Montgomery-Asberg Depression Rating Scale (MADRS) is a clinician-administered questionnaire that is widely used to assess the severity of depression symptoms in individuals. Stuart Montgomery and Asbjorn Sberg created it in 1979, and it has undergone several revisions since then. The MADRS comprises ten items, each of which is scored from 0 to 6, for a total score that can vary from 0 to 60. The questions include a variety of depressive symptoms, such as outward signs of melancholy, reported feelings of sadness, internal tension, decreased appetite, sleep reduction, attention problems, lethargy, an inability to feel, gloomy thoughts, and suicidal thoughts. The MADRS can be used to track changes in symptoms over time and is intended to evaluate the severity of depressive symptoms in individuals. It is commonly employed in clinical trials and research investigations to assess the efficacy of different depression therapies.[108]

The MADRS has been established to be a valid and useful tool for measuring depressive symptoms, with high levels of internal consistency and inter-rater reliability. It has also been demonstrated to be sensitive to changes in the course of depressive symptoms. The MADRS also focuses greater emphasis on cognitive and emotional symptoms than physical symptoms, making it less susceptible to clinician bias than certain other depression rating measures. Despite its strengths, the MADRS also has some limitations. One of the main limitations is its brevity, which may limit its sensitivity to detect changes in specific domains of depression. Additionally, some of the items on the MADRS, such as the item on suicidal thoughts, may require careful clinical judgment to assess. Overall, the MADRS has been extensively utilized in clinical and research contexts and is a good measure for determining the severity of depressive symptoms. To offer a thorough assessment of a person's depression, it must always be used in concert with other measures and clinical examinations. [109]

- **Social Problem-Solving Inventory-Revised (SPSI-RTM)**

A self-report questionnaire called the Social Problem-Solving Inventory-Revised (SPSI-R) is used to assess a person's social problem-solving skills. Thomas D'Zurilla and Arthur Goldfried created it in the 1970s, and it was updated in 2002. The 52 items that make up the SPSI-R are broken down into five subscales: avoidance style, impulsivity/carelessness style, rational problem solving, positive problem orientation, and negative problem orientation. A 5-point Likert scale with a scale of 0 (not at all true of me) to 4 (very true of me) is used to score each item. The subscales assess many facets of problem-solving, including the capacity for coming up with other solutions, the propensity to avoid issues, and the propensity to behave rashly or recklessly. The SPSI-R is designed to assess an individual's ability to solve social problems effectively and can be used to identify areas where the individual may need additional support or training. It can also be used to monitor changes in an individual's problem-solving abilities over time.

The SPSI-R has been proven to be a viable and reliable tool for evaluating problem-solving abilities. It is reliable between tests and has strong internal consistency. Additionally, it has been demonstrated to be sensitive to alterations in problem-solving skills over time. Since the SPSI-R is a self-report tool, people might not be completely truthful about their problem-solving abilities or might be subject to social desirability bias. Additionally, the SPSI-R may not be as effective in measuring problem-solving abilities in individuals with severe mental health disorders. Overall, the SPSI-R is a good way to measure how well people can solve problems in social settings. It can be used in both clinical and research settings. However, it should always be used in conjunction with other tests and clinical evaluations to get a full picture of a person's problem-solving skills. [110]

- **Behaviour Assessment System for Children (BASC)**

  The Behavior Assessment System for Children (BASC) is a multi-method, multi-informant tool used to assess the behavior and emotional functioning of children and adolescents aged 2–25 years. The BASC was developed by Cecil Reynolds and Randy Kamphaus in 1992 and has undergone several revisions since then. The BASC consists of several components, including a self-report questionnaire for children and adolescents, a parent questionnaire, and a teacher questionnaire. The self-report questionnaire is used for individuals aged 8–25 years, while the parent and teacher questionnaires are used for children aged 2–25 years. The questionnaire items cover a wide range of behaviors and emotions, including hyperactivity, aggression, anxiety, depression, social skills, and adaptive behaviors. The BASC also includes a structured behavioral observation component, which is used to assess specific problem behaviors in a naturalistic setting. This component allows for direct observation of the child's behavior and can provide more objective information about specific behaviors than self-report or informant-report measures. In addition to the questionnaires and observation component, the BASC includes a clinical interview guide and a behavior rating scale, which can be used to obtain additional information about the child's behavior and emotional functioning.

  The BASC is meant to give a full picture of a child's behavior and emotional health in different settings and with different people. It is often used in clinical and educational settings to find problem areas and make plans for how to fix them. The BASC can also be used to monitor progress over time and evaluate the effectiveness of interventions. The Behavior and Emotional Functioning Scale (BASC) is a valid and reliable way to measure behavior and emotional functioning, with good test-retest reliability and internal consistency. It has also been shown to be sensitive to changes in behavior and emotional functioning over time. However, like any assessment tool, the BASC is not perfect and has some limitations. One of its main limitations is that it relies on an informant report, which can be subject to bias and may not accurately reflect the child's behavior in all settings. Overall, the BASC is a useful tool for assessing behavior and emotional functioning in children and adolescents and can provide valuable information for clinical and educational decision-making. However, it should always be used in conjunction with other measures and clinical evaluations to provide a comprehensive assessment of the child's behavior and emotional functioning. [111]

- **Child Behaviour Checklist (CBCL)**

  A popular instrument for evaluating emotional and behavioral issues in kids and teenagers aged 6 to 18 is the Child Behaviour Checklist (CBCL). Thomas Achenbach created the CBCL in the 1980s, and it has subsequently undergone several changes. The CBCL consists of a series of questions that are completed by the child's parent or caregiver. The questions cover a wide range of emotional and behavioral problems, including anxiety, depression, aggression, hyperactivity, and social problems. The CBCL also includes several items that assess adaptive functioning, such as the child's ability to communicate with others and follow rules. The CBCL is designed to provide a comprehensive assessment of a child's emotional and behavioral problems and can be used to identify areas of concern and develop appropriate interventions. It is frequently used in clinical and educational settings to assess the severity of emotional and behavioral problems, monitor progress over time, and evaluate the effectiveness of interventions.

  The CBCL is a viable and accurate method for assessing emotional and behavioral issues. It is reliable between tests and has strong internal consistency. It has furthermore been demonstrated to be responsive to changes in behavioral and emotional issues throughout time. The fact that the CBCL depends on parent or carer reports, which might be biased and may not fully reflect the child's behavior in all circumstances, is one of its limitations. Additionally, evaluating emotional and behavioral issues in kids with intellectual or developmental impairments may not be as accurate using the CBCL. The CBCL is an effective tool for identifying emotional and behavioral issues in kids and teenagers, and it can offer important data for clinical and educational decision-making. To offer a thorough assessment of the child's emotional and behavioral functioning, it must always be used in conjunction with other measures and professional examinations.[112]

- **Beck Hopelessness Scale (BHS)**

  A psychological diagnostic instrument used to gauge someone's level of despair is the Beck Despair Scale (BHS). The BHS, a 20-item self-report questionnaire created by Aaron T. Beck in 1974, is intended to assess three primary characteristics of hopelessness: thoughts about the future, lack of drive, and expectations. Every question on the scale asks the respondent to rate a statement about the future or their sentiments on a range of 0 to 2, with 0 representing "false," 1 representing "partially true," and 2 representing "true." A total score is then calculated from 0 to 20, with higher values indicating greater pessimism.

  Since hopelessness is a major component of both depression and suicidal ideation, the BHS is frequently used to screen for these conditions. In many different contexts, including clinical and research settings, it has been demonstrated to be a valid and accurate measure of despair. It is crucial to remember that the BHS should be used in conjunction with other evaluation measures as well as clinical judgment because it is the only tool available for determining a person's level of hopelessness. It is not a diagnostic tool, and a high score on the BHS does not necessarily mean that an individual is suicidal or depressed. Overall, the BHS can be a useful tool for mental health professionals to assess an individual's level of hopelessness and guide treatment planning.[113]

- **Quick Inventory of Depressive Symptomatology-Self-Report (QID-SR)**

An evaluation technique used in psychology called the Quick Inventory of Depression Symptomatology-Self-Report (QID-SR) is used to gauge how severe depression symptoms are in people. It is based on the lengthier Inventory of Depressive Symptomatology (IDS), which Rush et al. established in 2003. The QID-SR is a 16-item self-report questionnaire created to evaluate the presence and severity of nine distinct symptoms of depression: depressed mood, difficulty concentrating or making decisions, suicidal thoughts, lack of interest in activities, energy or fatigue, feelings of guilt, changes in appetite or weight, and sleep disturbance. The four statements for each item on the scale demonstrate escalating levels of severity. The participant chooses the sentence that most accurately sums up their prior week. Each response option receives a score between 0 and 3 on a scale. More severe depressive symptoms are indicated by higher scores.

The QID-SR can be used to screen for depression or track therapy effectiveness. In several contexts, including clinical and research settings, it has been demonstrated to be a valid and accurate measure of depressed symptoms. It is crucial to remember that the QID-SR should be used in conjunction with other assessment instruments as well as clinical judgment because it is the only tool available for determining a person's level of depression. It is not a diagnostic instrument, and a high QID-SR score does not imply that someone is clinically depressed. Overall, the QID-SR can help mental health providers determine the severity of depressed symptoms and inform treatment decisions.[114]

- **Patient Health Questionnaire (PHQ-9)**

Adults can use the Patient Health Questionnaire (PHQ-9) on their own to determine whether they are depressed and how severe depression is. Drs. Robert L. Spitzer, Janet B.W. Williams, Kurt Kroenke, and others created it in 1999. The PHQ-9 measures nine of the symptoms of major depression that are listed in the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV). In response to the questions, the respondent is asked how frequently they have experienced depressive symptoms over the previous two weeks, such as loss of interest or enjoyment, feelings of sadness or hopelessness, changes in appetite or weight, sleep disturbances, fatigue, feelings of worthlessness or guilt, difficulty concentrating, and thoughts of death or suicide. The scores for each question range from 0 to 3, with higher scores indicating more severe indicators of depression. A total score ranging from 0 to 27 is generated by adding the scores for each item. With a total score of 5 to 9, depression is categorized as mild, 10 to 14, moderate, 15 to 19, moderately severe, and 20 to 27, severe.

The PHQ-9 is a popular and reliable indicator of the severity of depression. It is frequently used as a depression screening tool in primary care settings and can assist doctors in deciding if more examination or therapy is required. Additionally, it may be used to track how well a treatment is working and evaluate how depression symptoms evolve. It is crucial to remember that the PHQ-9 should be used in conjunction with other assessment instruments as well as clinical judgment because it is the only tool available for determining a person's level of depression. A clinical diagnosis should be done by a qualified mental health practitioner because a high PHQ-9 score does not guarantee that a person has clinical depression. The PHQ-9 can be a helpful tool for primary care physicians and mental health professionals to rapidly and easily evaluate the severity of depression symptoms in their patients. [115][116]

- **Reminiscence Functions Scale (RFS)**

A psychological test called the Reminiscence Functions Scale (RFS) analyses the functions or causes behind people's reminiscing, which is the act of reflecting on and recalling the past. The RFS was created by Webster in 1993 and is often applied in both clinical and research contexts. The 43 questions that make up the RFS assess the various goals or motivations behind why people recall things. Reduced boredom, identity building, problem-solving, death preparation, dialogue, closeness maintenance, bitterness revival, and memory/sensory stimulation are among the functions evaluated.

A reason for recalling past events is presented for each item on the scale, such as "to gain insight into who I am now" or "to remember pleasant experiences." On a 4-point Likert scale, from 1 (not at all important) to 4 (extremely important), the subject is asked to score the statement. Higher scores imply a function's relevance in the subject's memory, and the responses are then totaled up to produce a total score for each of the seven functions. The RFS may also be used to determine a person's total score for how important memories are to them. It has been discovered that the RFS is a valid and reliable indicator of recollection functions in a range of groups, including older adults and those with dementia. It may be utilized as a tool to comprehend the function of remembrance in various circumstances or as a guide for reminiscence-based therapies. Overall, the RFS can help academics and mental health providers better understand why people recollect and develop therapies that are tailored to their unique needs.[117]

- **Short Form Health Survey (SF-36)**

  People can self-complete the Short Form Health Survey (SF-36) to learn more about their overall health and quality of life. One of the most extensively used health-related quality-of-life measures worldwide, it was created by John E. Ware and colleagues in the late 1980s. The 36 items on the SF-36 examine eight different aspects of health: physical functioning, role limits brought on by physical health issues, body pain, general health perceptions, vitality, social functioning, role restrictions brought on by emotional issues, and mental health. The responder is asked to rate how much they agree or disagree with each of the statements regarding their health and well-being during the last four weeks.

  With 0 representing the poorest health state and 100 representing the greatest, the responses are then used to calculate scores for each of the eight domains. The results can be used to assess the health status of a person about that of the general population and to monitor changes in health status over time. The SF-36 includes two summary scores in addition to the eight domain scores: the Physical Component Summary (PCS) and the Mental Component Summary (MCS).

The domain scores are weighted by their significance in predicting physical and mental health, respectively, to determine these scores. In a variety of groups and situations, including clinical trials, epidemiological investigations, and general population surveys, the SF-36 has been demonstrated to be a valid and reliable indicator of health-related quality of life. It may be applied to compare the health state of various populations and track changes in health status over time. It can also be used to evaluate the effectiveness of health treatments. Overall, the SF-36 is a widely accepted and thoroughly researched indicator of health-related quality of life that can reveal important details about a person's health and well-being. [118]

- **Social Adjustment Scale-Self Report (SAS-SR)**

The Social Adjustment Scale-Self Report (SAS-SR) is a psychological assessment tool used to measure an individual's level of social adjustment. It is a self-report questionnaire consisting of 54 items that assess various aspects of an individual's social functioning. The SAS-SR was developed in 1964 by psychiatrist David C. Dohrenwend and his colleagues, and it has since been widely used in both clinical and research settings to assess social adjustment in individuals with psychiatric disorders, medical illnesses, and other conditions that may affect social functioning. The SAS-SR looks at work, leisure, marital and family relationships, and social activity, among other things. It has questions that measure a person's ability to make and keep relationships, deal with stress, and work well in different social situations.

On the SAS-SR, each item is graded on a five-point scale that goes from "very well" to "very poorly." The respondent is asked to rate how well they are currently functioning in various social situations, and the scores are then tallied to provide an overall score for social adjustment. The SAS-SR is a reliable and valid tool for assessing social adjustment in a wide range of populations, including people with psychiatric disorders, medical illnesses, and healthy people. It has been used in research studies to examine the impact of different interventions on social adjustment, as well as to identify factors that may contribute to poor social adjustment. Overall, the SAS-SR is a useful tool for clinicians and researchers who are interested in assessing an individual's level of social adjustment and identifying areas where they may need additional support or intervention.[119]

- **Social Functioning Questionnaire (SFQ)**

  The Social Functioning Questionnaire (SFQ) is a self-reporting questionnaire used to figure out how well a person gets along with other people. It was developed by David Goldberg and his colleagues in 1970 and has been widely used in research and clinical settings to assess social functioning in individuals with mental health disorders. The SFQ has 30 questions, and each one has a response range of 0 to 3, where 0 means the behavior or symptom is not present and 3 means the behavior or symptom is at its worst. The questionnaire measures different parts of a person's social functioning, such as their ability to talk to others, make and keep friends, and take part in social activities. The SFQ looks at work, leisure, marital and family relationships, and social activities, among other things. It has questions that measure a person's ability to start and keep social relationships, deal with stress, and work well in different social situations.

  The Social Functioning Questionnaire (SFQ) is a reliable and valid way to measure social functioning in a wide range of people, including those with psychiatric disorders, medical illnesses, and healthy people. It has been used in research studies to examine the impact of different interventions on social functioning, as well as to identify factors that may contribute to poor social functioning. Overall, the SFQ is a useful tool for clinicians and researchers who are interested in assessing an individual's level of social functioning and identifying areas where they may need additional support or intervention.[120]

- **Geriatric Depression Scale (GDS)**

To determine if an elderly person is depressed, a screening instrument called the Geriatric Depression Scale (GDS) is utilized. It was created in 1983 by Yesavage and colleagues and is now a popular instrument for determining depression in older persons. Each of the 30 items on the GDS has a yes/no response choice. The questionnaire gauges a person's mood in a variety of ways, including their level of despair, hopelessness, guilt, and helplessness. Additionally, it evaluates bodily symptoms such as weariness, altered appetite, and disturbed sleep. It has been determined that the GDS is a viable and reliable instrument for evaluating depression in older persons. It has been used to screen for depression and track changes in depressed symptoms over time in clinical and research settings. In addition, the GDS has been used to detect functional impairment, social isolation, and chronic medical disorders as risk factors for depression in older persons.

The GDS has been modified to allow it to be utilized with a variety of populations, including those who have dementia and those from other cultures. A 15-item short form of the GDS is also available, with a yes-or-no response choice. In general, physicians and academics who are interested in evaluating depression in older persons will find the GDS to be a valuable instrument. It offers a rapid and efficient technique to screen for depression in this group and is simple to administer and score. However, if depression is suspected, a comprehensive clinical assessment should be carried out and it should not be used as a diagnostic tool on its own. [121]

- **Life Satisfaction Index**

  An independent survey called the Life Satisfaction Index (LSI) is used to gauge people's level of happiness with their lives. It was created by Neugarten and colleagues in 1961 and has since grown in popularity as a method for gauging people's levels of life satisfaction. The LSI consists of 20 questions that examine several aspects of a person's life, including their social relationships, place of employment, state of health, and sense of overall meaning and purpose. On a scale from 1 (extremely unsatisfied) to 7 (very satisfied), respondents are asked to assess their degree of satisfaction with various elements of their lives. It has been determined that the Life Satisfaction Inventory (LSI) is a viable and reliable method for assessing life satisfaction in a variety of populations, including older persons, those with chronic diseases, and those from other cultures. It has been used in studies to look at the effects of various treatments on life satisfaction as well as to find potential causes of reduced life satisfaction.

By accounting for all the various aspects of life that impact overall pleasure, the LSI provides a complete picture of a person's level of life satisfaction. It is a helpful tool for physicians and academics who are interested in figuring out how satisfied someone is with their life and where they might need more assistance or intervention. In general, the LSI is a useful tool for gauging life satisfaction and may reveal a lot about a person's well-being and standard of living. It should be used in conjunction with other assessment tools and professional examinations to provide a complete picture of a person's health because, like other self-report surveys, it may be biased. .[122] [123]

2.5 Research Gap

A pervasive and severe mental illness that impacts millions of individuals globally is depression. It is defined by enduring depressive and dismal feelings as well as a lack of enthusiasm or enjoyment in routine activities. A person's thoughts, feelings, and physical health can all be profoundly impacted by depression, which can result in a variety of symptoms and limitations in day-to-day functioning. In the past, the psychiatrist diagnosed depression through face-to-face communication and patient contact. The patient's conduct and mood fluctuations are also used to diagnose this illness. As times have changed, a variety of depression detection methods have become available to determine whether a person is depressed or not, as well as what kind of depression the patient is experiencing. It has been noted that the tools the psychiatrist utilised are built around survey questions. The survey's questions are based on limitations of all the currently available tools. A psychiatrist has assisted in the development of a questionnaire for this study that focuses on both the positive and negative aspects of each person's daily routine and existence. Additionally, a weekly sentiment poll that captures each person's mood for a week is added. The tool is intended to determine the degree of depression with the use of machine learning techniques.

CHAPTER 3

Research methodology

This chapter outlines three sections which include the adopted procedure for detecting depression with the help of machine learning techniques (see Figure 3.1)According to a poll conducted in 2021, depression affects over 280 million individuals in the nation and is the leading cause of illness and injury. A mental health condition that affects millions of individuals worldwide, depression is one of the most prominent. Major depression can be prevented from developing by early recognition of its signs, prompt intervention, and therapy. This has made it necessary to employ various cutting-edge methods for the identification of depression in order to assist medical professionals in correctly identifying and treating depression. Online posts, audio files, video files, and facial expressions can all be used to study depression.[124]

Depression is a chronic, all-encompassing illness rather than just a transient state of sadness. Typical signs and symptoms include: Prolonged melancholy or depression, loss of enjoyment or interest in previously enjoyed activities, alterations in weight or appetite, sleep disorders (oversleeping or sleeplessness), exhaustion and low vitality, Feelings of remorse or worthlessness, Trouble focusing or making decisions, recurring suicidal or fatal ideas [125].

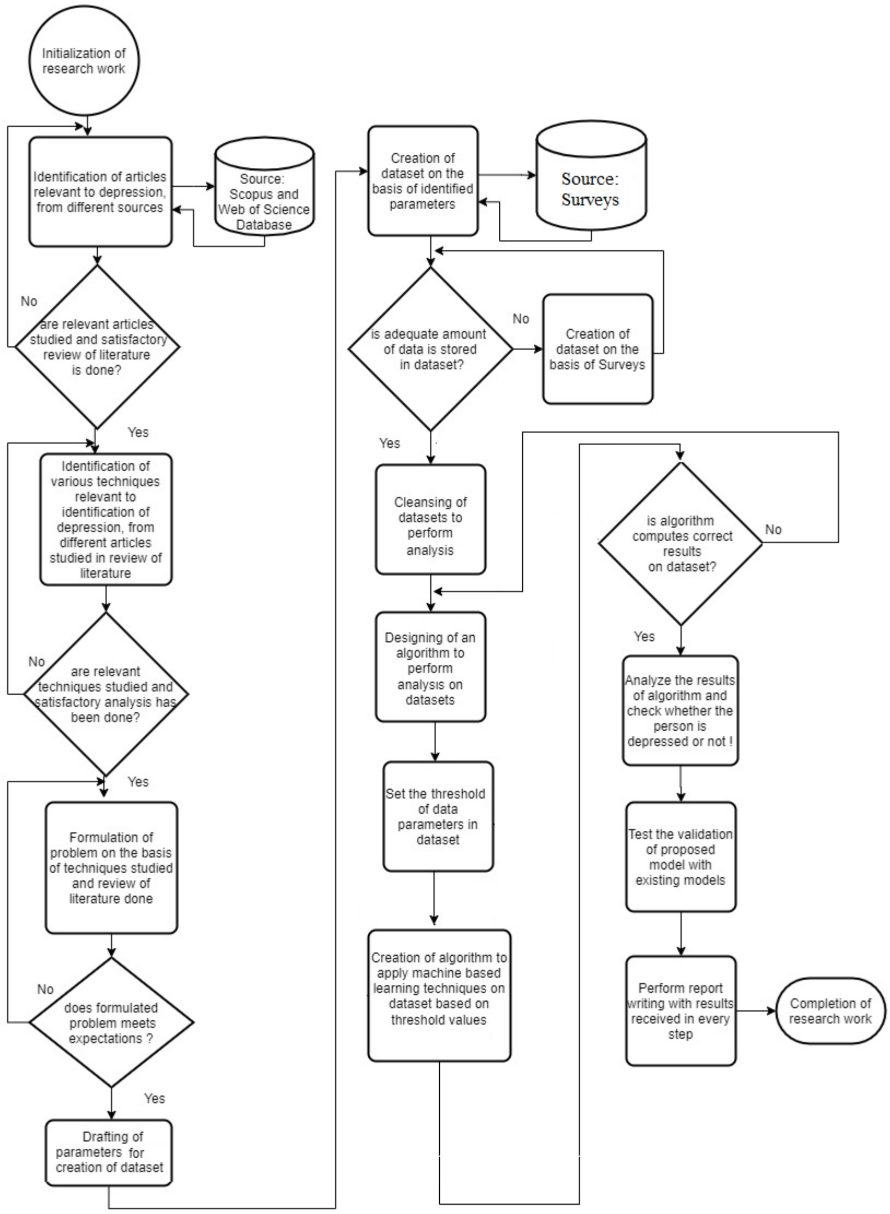


FIGURE 3.1: *Flow chart depicting the description of the performed study.*

Data collection was one of the tasks that were carried out during the first stage of the study project. The material that was compiled came from several different sources and was provided by people of varying ages. In the second stage of the process, machine learning was utilized, which resulted in the creation of a system that enables users to respond to a questionnaire that is based on their activities and many aspects of their personal lives. This stage of the process allowed for the establishment of the system. During the third phase, a website was established that enabled end users to assess the level of depression that an individual was feeling and submit their responses to the questionnaire.

3.1 Data collection

Depression can be diagnosed based on a lot of different things, but the most important ones are the person's level of education, age, annual income, marital status, and several other factors. Many different traits can affect the diagnosis of depression.

The issues that have been brought up until this point have each played a part in the growing prevalence of depression in India. In light of this issue, the current research investigates a proposed questionnaire which is designed by the psychiatrist which consist of questions based on personal details, behaviour and mood swings of an individual. Additionally, a technical solution is discovered to encourage the detection of sadness by making use of techniques related to machine learning. The processes and procedures that were followed in the building of a website that is concentrated on the detection of depression are outlined in this chapter. The website in question is focused on the diagnosis of depression. The purpose of this research is to establish a method for evaluating the degree to which an individual suffers from depression.

To do this, recent data from a wide range of sources has been gathered, looked at, and then put into words. For this applied study, we got information from a total of 1694 people who lived in many different countries, states, and other administrative divisions. The data has been collected through an open-ended questionnaire that includes various parameters as shown in Table 3.1 and Table 3.2.

3.1.1 Questionnaire detail

- **Losing interest in social activities:**

  One of the common symptoms of depression is a loss of interest in social activities. This means that people with depression may not enjoy the activities or hobbies they once enjoyed and may not feel motivated to participate in social events or spend time with friends and family. This symptom is also known as anhedonia, which refers to the inability to experience pleasure or joy. In depression, anhedonia can make it difficult for people to feel motivated to engage in activities that they used to enjoy. It can also make it harder for them to feel connected to others, as they may not feel the same level of enjoyment or connection that they once did.

Losing interest in social activities can be a significant challenge for people with depression, as it can lead to isolation, loneliness, and a sense of disconnection from the world around them. It can also make depression symptoms worse, like a bad mood, a lack of energy, and feeling like there is no hope. Treatment for depression often involves addressing anhedonia and helping people re-engage with activities and social connections that can bring them pleasure and fulfillment. This may involve trying new hobbies, rekindling old interests, or finding new ways to connect with others. Therapy, medication, and other interventions can also be effective in reducing the symptoms of depression and helping people regain their interest in social activities.

- **Loss of Energy or excessive tiredness:**

  One of the common symptoms of depression is a loss of energy or excessive tiredness, which is also known as fatigue. This symptom can show up in several ways, such as feeling physically tired, having trouble getting out of bed in the morning or feeling like even small tasks take a lot of work. Fatigue in depression is different from the normal tiredness that we all experience from time to time. People with depression may feel tired even after a full night's sleep and may find that their fatigue does not improve with rest or relaxation. This can make it difficult to complete tasks at work or home and can contribute to a sense of hopelessness and helplessness.

  The exact causes of fatigue in depression are not well understood, but they are believed to be related to changes in brain chemistry and disruptions in the body's stress response system. Depression can also cause changes in how you sleep, which can make you feel even more tired and lethargic. Treating fatigue in depression typically involves addressing the underlying symptoms of depression itself. This may involve therapy, medication, or a combination of both. In addition, several strategies can help to manage fatigue and boost energy levels, such as getting regular exercise, improving sleep hygiene, and practicing stress management techniques like mindfulness or relaxation exercises. It is important to talk to a healthcare professional if you are experiencing symptoms of depression, including fatigue, as they can help develop an individualized treatment plan that meets your specific needs.

- **Losing excitement in activities that used to excite earlier:**

  One of the common symptoms of depression is losing excitement in activities that used to bring pleasure and enjoyment. This sign is also called anhedonia, which means not being able to feel pleasure or happiness. When people experience anhedonia in depression, they may find that activities or hobbies that used to excite or inspire them no longer hold the same appeal. They may feel apathy, disinterest, or a lack of motivation to do things they used to enjoy. This can include things like hobbies, going out with friends, and even things like work or doing chores around the house.

  When someone with depression loses interest in things they used to enjoy, it can be upsetting because it can make them feel empty or numb. It can also make it hard to enjoy or find meaning in life, which can make depressive symptoms even worse. Treatment for anhedonia in depression often involves addressing the underlying symptoms of depression itself. This may involve therapy, medication, or a combination of both. Additionally, behavioral activation therapy, a specific type of therapy for depression, focuses on helping people identify activities that they find meaningful and enjoyable and gradually reintroduce these activities into their lives. This can help improve mood, increase motivation, and reduce symptoms of depression over time. It's important to remember that anhedonia in depression is a common symptom that can be managed with appropriate treatment and support. If you or someone you know is experiencing symptoms of depression, including anhedonia, it's important to talk to a healthcare professional for guidance and support.

- **Prefer sitting alone:**

  One of the most common signs of depression is wanting to be alone or pulling away from social activities. People with depression may find that they prefer sitting alone or spending time in solitude rather than engaging in social activities or spending time with others. There are many potential reasons for this symptom. Depression can cause feelings of fatigue or exhaustion, which may make it difficult for people to engage in social activities. It can also cause feelings of sadness, hopelessness, or low self-esteem, which can contribute to a sense of social disconnection or a belief that others won't understand or support them.

  Isolating yourself from other people may also be a way to deal with the overwhelming feelings and thoughts that can come with depression. People with depression may feel safer or more comfortable when they are alone. This is because being alone can give them a sense of control or familiarity in a world that is otherwise scary or confusing. While social isolation may provide temporary relief or comfort, it can also exacerbate the symptoms of depression over time. Social support is an important factor in managing depression, and spending time with others can help to improve mood, increase feelings of connection and belonging, and reduce feelings of loneliness and isolation. Treatment for depression often involves addressing social isolation as a symptom as well as the underlying causes of depression itself. Therapy, medication, and other interventions can be effective in reducing symptoms of depression and helping people re-engage with social activities and relationships. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including a preference for social isolation.

- **Less interactive as per people's point of view:**

A decreased level of social interaction or engagement with others is one of the typical symptoms of depression, according to other people. People with depression may appear less responsive or engaged in social interactions than they used to be and may be perceived as distant, uninterested, or disengaged. There are many potential reasons for this symptom. Depression can cause feelings of sadness, low self-esteem, and hopelessness, which can make it difficult for people to engage with others. It can also cause fatigue or a lack of energy, which can make social interactions feel more challenging or draining.

In addition, depression can affect cognitive function and the ability to process information, which can make it difficult to participate in conversations or engage with others in meaningful ways. People with depression may find that they struggle to focus or concentrate, or that their thoughts feel slow or disconnected. It's important to note that this symptom is typically a subjective observation made by others rather than an objective measure of social engagement. People with depression may still feel a desire for social interaction but may be inhibited by the symptoms of depression. Treatment for depression often involves addressing social interaction as a symptom as well as the underlying causes of depression itself. Therapy, medication, and other interventions can be effective in reducing symptoms of depression and helping people re-engage with social activities and relationships. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including a perceived decrease in social interaction.

- **Persistently feels sadness of mood:**

  One of the primary symptoms of depression is a persistent feeling of sadness or a low mood that persists over an extended period. This symptom can be characterized by feelings of hopelessness, despair, and a lack of enjoyment or pleasure in activities that used to bring pleasure. It's important to note that feelings of sadness are a normal part of the human experience, and it's not uncommon for people to feel sad or low from time to time. However, in depression, the feelings of sadness persist for a prolonged period (usually two weeks or longer) and can interfere with daily life.

People with depression may feel like their emotions are out of their control and may struggle to find joy or meaning in activities that they used to enjoy. They may also experience physical symptoms such as fatigue, changes in appetite or sleep patterns, and a lack of energy or motivation. The experience of persistent sadness can be distressing and contribute to a sense of hopelessness or despair. It can also make it difficult to engage in daily activities, maintain relationships, and perform at work or school. Treatment for depression often involves a combination of therapy, medication, and lifestyle changes. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns that contribute to feelings of sadness and hopelessness. Medications, such as antidepressants, can also be helpful in reducing symptoms of depression and improving mood. If you or someone you know is experiencing persistent feelings of sadness or a low mood, it's important to talk to a healthcare professional for guidance and support. Depression is a treatable condition, and with the right treatment and support, people can go on to lead fulfilling and meaningful lives.

- **Often noticed having frequent crying spells:**

One of the common symptoms of depression is frequent crying spells, which can be characterized by sudden and intense bouts of crying, often without an apparent trigger. These crying spells can occur in response to a wide range of stimuli, including sad or stressful events as well as seemingly minor triggers. It's important to note that crying is a normal human response to emotional distress, and it's not uncommon for people to cry from time to time. However, in depression, the frequency and intensity of crying spells may be more pronounced and can interfere with daily life. People with depression may feel like they are unable to control their emotions or that they are experiencing them more intensely than usual. Crying spells can be triggered by a wide range of stimuli and may occur even in situations where the person would not typically expect to cry.

Crying spells can be distressing and can contribute to a sense of hopelessness or despair. They can also make it difficult to engage in daily activities, maintain relationships, and perform at work or school. Treatment for depression often involves a combination of therapy, medication, and lifestyle changes. Therapy can help people develop coping skills to manage their emotions and identify triggers that may contribute to crying spells. Medications, such as antidepressants, can also help reduce symptoms of depression and stabilize mood. If you or someone you know is experiencing frequent crying spells or other symptoms of depression, it's important to talk to a healthcare professional for guidance and support. Depression is a treatable condition, and with the right treatment and support, people can go on to lead fulfilling and meaningful lives.

- **Less Confident:**

  One of the common symptoms of depression is feeling less confident, which can be characterized by a decrease in self-esteem, self-worth, and self-assurance. People with depression may feel like they are not good enough, worthless, or a burden to others. The experience of feeling less confident can be distressing and can contribute to a sense of hopelessness or despair. It can also make it difficult to engage in daily activities, maintain relationships, and perform at work or school. There are many potential reasons for feeling less confident in the face of depression. Depression can cause negative thought patterns and cognitive distortions that can contribute to feelings of low self-worth. People with depression may also experience physical symptoms, such as fatigue or a lack of energy, that can make it difficult to feel confident or capable.

  It's important to note that feeling less confident is a symptom of depression and is not necessarily reflective of a person's actual abilities or worth. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase their self-esteem. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve mood, which can in turn improve feelings of confidence and self-worth. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including a decrease in confidence and self-esteem.

- **Facing difficulties in planning and executing tasks:**

  One of the common symptoms of depression is difficulty planning and executing tasks, which can make it challenging to manage daily responsibilities and meet personal goals. This symptom can be characterized by a lack of motivation, difficulty concentrating, and trouble with memory and decision-making. People with depression may find it difficult to complete tasks or initiate new ones. They may feel overwhelmed by even simple tasks or struggle to organize their thoughts and prioritize their responsibilities. This can result in a sense of helplessness as well as guilt or shame for not being able to meet personal expectations.

  There are many potential reasons for difficulty in planning and executing tasks in depression. Depression can cause changes in brain chemistry that can impact cognitive function, including decision-making and memory. People with depression may also experience physical symptoms, such as fatigue or a lack of energy, that can make it difficult to initiate and complete tasks. It's important to note that difficulty in planning and executing tasks is a symptom of depression and is not necessarily reflective of a person's abilities or motivation. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase motivation. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve motivation and concentration. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including difficulty planning and executing tasks.

- **Have you become indecisive:**

  One of the common symptoms of depression is indecisiveness, which can be characterized by difficulty making decisions and a lack of confidence in one's ability to make choices. People with depression may struggle with even small decisions, such as what to wear or what to eat, and may feel overwhelmed by larger decisions, such as career or relationship choices. There are many potential reasons for indecisiveness in depression. Depression can cause changes in brain chemistry that can impact cognitive function, including decision-making and memory. Negative thought patterns and cognitive distortions can also contribute to feelings of indecisiveness and uncertainty. Additionally, physical symptoms of depression, such as fatigue or a lack of energy, can make it difficult to concentrate and make decisions.

  Indecisiveness can be distressing and can contribute to a sense of hopelessness or despair. It can also make it difficult to engage in daily activities, maintain relationships, and perform at work or school. Treatment for depression often involves a combination of therapy, medication, and lifestyle changes. Therapy can help people develop coping skills to manage negative thoughts and increase their self-confidence. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve cognitive function, including decision-making. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including indecisiveness.

- **Facing concentration issues:** One of the common symptoms of depression is difficulty with concentration, which can make it challenging to focus on tasks or engage in activities. This symptom can be characterized by a lack of focus, destructibility, and forgetfulness. People with depression may find it difficult to concentrate on tasks or engage in activities that they once found enjoyable. They may struggle with completing work assignments, remembering details, or following through on plans. This can result in a sense of frustration as well as guilt or shame for not being able to meet personal expectations.

There are many potential reasons for difficulty with concentration in depression. Depression can cause changes in brain chemistry that can impact cognitive function, including attention and memory. Negative thought patterns and cognitive distortions can also contribute to feelings of destructibility and forgetfulness. Additionally, physical symptoms of depression, such as fatigue or a lack of energy, can make it difficult to stay focused and engaged. It's important to note that difficulty with concentration is a symptom of depression and is not necessarily reflective of a person's abilities or motivation. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase focus. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve cognitive function, including attention and memory. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including difficulty with concentration.

- **Persistently Feeling of self-worthlessness:** One of the common symptoms of depression is a persistent feeling of worthlessness, which can be characterized by a sense of low self-esteem, self-criticism, and self-blame. People with depression may feel like they are worthless, unlovable, or a burden to others. This feeling of worthlessness can contribute to a sense of hopelessness or despair and may make it difficult to engage in daily activities or maintain relationships. People with depression may withdraw from social interactions or avoid activities that they once found enjoyable.

  There are many potential reasons for the feeling of worthlessness in depression. Depression can cause changes in brain chemistry that can impact mood and self-esteem. Negative thought patterns and cognitive distortions can also contribute to feelings of self-criticism and self-blame. Additionally, external factors such as stress, trauma, or difficult life events can also contribute to feelings of worthlessness. It's important to note that a feeling of worthlessness is a symptom of depression and is not necessarily reflective of a person's true worth or value. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase their self-esteem. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve mood and self-esteem. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including feelings of worthlessness.

- **Feeling of empty and emotional numbing:**

  Feelings of emptiness and emotional numbing are common symptoms of depression and can be characterized by a sense of apathy, disconnection, and a lack of emotional responsiveness. People with depression may feel like they are going through the motions of daily life without experiencing any real sense of pleasure or meaning. This feeling of emptiness can contribute to a sense of hopelessness or despair and may make it difficult to engage in daily activities or maintain relationships. People with depression may withdraw from social interactions or avoid activities that they once found enjoyable. They may also have difficulty expressing emotions or feeling connected to others. There are many potential reasons for the feeling of emptiness and emotional numbness in depression. Depression can cause changes in brain chemistry that can impact mood and emotional regulation. Negative thought patterns and cognitive distortions can also contribute to feelings of apathy and disconnection. Additionally, external factors such as stress, trauma, or difficult life events can also contribute to feelings of emotional numbness.

It's important to note that feelings of emptiness and emotional numbing are symptoms of depression and are not necessarily reflective of a person's true emotional capacity. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase emotional responsiveness. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve emotional regulation. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including feelings of emptiness and emotional numbing.

- **Feeling of hopelessness:**

  A feeling of hopelessness is a common symptom of depression and can be characterized by a sense of despair, pessimism, and a belief that things will never get better. People with depression may feel trapped in a cycle of negative thoughts and emotions and struggle to see any hope or possibility for the future. This feeling of hopelessness can contribute to a sense of helplessness or powerlessness and may make it difficult to engage in daily activities or maintain relationships. People with depression may withdraw from social interactions or avoid activities that they once found enjoyable. They may also struggle with feelings of low self-esteem or self-worth.

  There are many potential reasons for the feeling of hopelessness in depression. Depression can cause changes in brain chemistry that can impact mood and emotional regulation. Negative thought patterns and cognitive distortions can also contribute to feelings of pessimism and hopelessness. Additionally, external factors such as stress, trauma, or difficult life events can also contribute to feelings of hopelessness. It's important to note that a feeling of hopelessness is a symptom of depression and is not necessarily reflective of a person's true situation or potential. People with depression may benefit from therapy and counseling to help them develop coping skills to manage negative thoughts and increase feelings of hope and optimism. Cognitive-behavioral therapy, in particular, can be effective in helping people identify and change negative thought patterns. Medications, such as antidepressants, can also help reduce symptoms of depression and improve mood and emotional regulation. It's important to talk to a healthcare professional if you or someone you know is experiencing symptoms of depression, including a feeling of hopelessness.

- **Do you feel that nobody understands you:**

  Feeling like nobody understands you is a common symptom of depression and can contribute to a sense of isolation, loneliness, and hopelessness. People with depression may feel like they are alone in their experiences and may struggle to find others who can relate to their feelings and emotions. This feeling of isolation can be particularly challenging because depression can also cause people to withdraw from social interactions and activities they once enjoyed. This can make it even harder to connect with others and find support during difficult times.

  It's important to remember that depression is a common and treatable condition and that many people have experienced similar feelings and emotions. Seeking help from a mental health professional or support group can be a valuable step in finding connection and understanding during depression. Therapists and support groups can provide a safe and non-judgmental space to talk about feelings, learn coping strategies, and connect with others who are going through similar experiences. It's also important to communicate openly and honestly with loved ones about how you are feeling. Although it can be challenging to talk about depression, sharing your experiences with trusted friends and family members can help reduce feelings of isolation and improve support networks. Loved ones may not always understand exactly what you are going through, but they can still offer compassion and support.

- **Do you have sleeping disturbance:**

Yes, sleeping disturbances are a common symptom of depression. People with depression may experience difficulty falling asleep, staying asleep, or waking up too early in the morning. They may also experience changes in sleep patterns, such as sleeping more than usual or less than usual. Sleep disturbances can be particularly challenging because they can contribute to fatigue, irritability, and difficulty concentrating during the day. Lack of sleep can also worsen symptoms of depression and make it more difficult to manage emotions and engage in daily activities.

Although the precise causes of sleep problems in depression are not completely known, it is believed that alterations in brain chemistry and hormone levels are responsible. Sleep issues may also be a result of depression-related stress and anxiety. To prevent further health issues and worsening of depression symptoms, it is crucial to manage sleep abnormalities in depression. Therapy, medicine, and lifestyle modifications such as bettering sleep hygiene (forming a regular sleep pattern, abstaining from stimulants like caffeine before bed, providing a relaxing environment for sleeping, etc.) may all be used as treatments for depression. If you are having trouble sleeping or are dealing with other depression-related symptoms, it's crucial to speak with a medical expert. They can assist you in creating a customized treatment plan to control your symptoms and enhance your general health.

- **Feeling changes in Appetite and Significant Weight loss :**

  Changes in appetite and significant weight loss are common symptoms of depression. Some people with depression may experience a decrease in appetite and lose weight as a result, while others may experience an increase in appetite and gain weight. These changes in appetite and weight can be particularly challenging because they can affect overall physical health and contribute to feelings of low self-esteem and poor body image. In some cases, significant weight loss can also indicate a more serious health condition, so it's important to talk to a healthcare professional if you experience sudden or unexplained weight loss.

The exact reasons for changes in appetite and weight in depression are not fully understood, but they are thought to be related to changes in brain chemistry and hormone levels. Stress and anxiety associated with depression can also contribute to changes in appetite and weight. It's important to address changes in appetite and weight in depression because they can worsen depressive symptoms and increase the risk of other health problems. Treatment for depression may include therapy, medication, and lifestyle changes such as improving nutrition and increasing physical activity. It's important to talk to a healthcare professional if you are experiencing changes in appetite, weight, or other symptoms of depression. They can help you develop a personalized treatment plan to manage your symptoms and improve your overall well-being.

- **Feeling often restless or being slowed:**

  Feeling restless or slowed down is a common symptom of depression. Some people with depression may feel agitated, fidgety, or restless, while others may feel like their movements and thoughts are slowed down. Restlessness can be particularly challenging because it can contribute to difficulty concentrating, irritability, and difficulty sleeping. On the other hand, feeling slowed down can make it more challenging to engage in daily activities and may lead to feelings of apathy or low motivation.

  The exact reasons for feeling restless or slowed down in depression are not fully understood, but they are thought to be related to changes in brain chemistry and hormone levels. Stress and anxiety associated with depression can also contribute to feelings of restlessness or slowing down. It's important to address feelings of restlessness or being slowed down in depression because they can worsen depressive symptoms and reduce quality of life. Treatment for depression may include therapy, medication, and lifestyle changes such as increasing physical activity and practicing relaxation techniques. It's important to talk to a healthcare professional if you are experiencing restlessness, being slowed down, or other symptoms of depression. They can help you develop a personalized treatment plan to manage your symptoms and improve your overall well-being.

- **Ever thought of attempting suicide (Deliberate self-harm/death wish/ ideation / made plans / attempted):**

  Thoughts of suicide or self-harm are a serious and potentially life-threatening symptom of depression. People with depression may experience thoughts of suicide or death, which can range from fleeting thoughts to detailed plans of self-harm or suicide attempts. Suicidal ideation refers to thoughts of suicide or the desire to take one's own life, while suicidal plans refer to specific details about how one would carry out a suicide attempt. Suicide attempts involve engaging in self-harm behaviors with the intent of causing serious harm or death to oneself.

  It's important to take thoughts of suicide or self-harm seriously and seek immediate help if you or someone you know is experiencing these symptoms. If you or someone you know is in crisis, call emergency services or go to the nearest emergency room. You can also call a suicide prevention hotline or talk to a healthcare professional for support and guidance. Treatment for depression may include therapy, medication, and other interventions to address suicidal ideation and prevent self-harm or suicide attempts. It's important to talk to a healthcare professional if you are experiencing thoughts of suicide, self-harm, or other symptoms of depression. They can help you develop a personalized treatment plan to manage your symptoms and improve your overall well-being.

- **Do you think these symptoms are present persistently for more than two weeks:**

  It's crucial to keep in mind that depression symptoms can last for a long time while discussing them. For a diagnosis of major depressive disorder, symptoms of depression must be present for at least two weeks, according to the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), which is a commonly used manual for making such diagnoses. This means that if a person experiences one or more symptoms of depression persistently for two weeks or more, it may be an indication of a depressive episode. However, it's important to note that a diagnosis of depression requires a comprehensive evaluation by a healthcare professional who can rule out other potential causes of the symptoms.

If you or someone you know is experiencing symptoms of depression that have persisted for more than two weeks, it's important to seek help from a healthcare professional. Treatment for depression may include therapy, medication, and lifestyle changes such as exercise, healthy eating, and stress reduction techniques. The sooner a person seeks help for depression, the more effective treatment may be in reducing symptoms and improving overall well-being.

- **Do you feel these symptoms have a significant impact on your Social / Occupational /Family or other important areas of your life:**

  Yes, symptoms of depression can have a significant impact on a person's life, including their social, occupational, and familial relationships, as well as other important areas of their life. In terms of social functioning, people with depression may withdraw from social activities, experience difficulty forming and maintaining relationships, and isolate themselves from friends and family members. They may also have difficulty communicating or expressing themselves, which can lead to further isolation and difficulty connecting with others.

  In terms of occupational functioning, people with depression may experience difficulties in performing their job duties, have difficulty concentrating, and have decreased productivity. They may also miss work or have difficulty attending work regularly, which can impact their income and job stability. Depression can also have a significant impact on familial relationships, including marriages, parenting, and other family dynamics. People with depression may have difficulty providing emotional support or may experience difficulty engaging with family members in activities. Overall, the symptoms of depression can impact all areas of a person's life, leading to a decrease in their overall quality of life. It's important for individuals experiencing symptoms of depression to seek help from a healthcare professional to manage their symptoms and improve their overall functioning.

- **Has Pet:**

  Many people choose to have a pet during the depression because of the numerous benefits that pets can provide. Pets, particularly dogs and cats, offer unconditional love and affection, which can help alleviate feelings of loneliness and isolation that often accompany depression. Pets also offer a sense of purpose and responsibility, which can help people suffering from depression feel needed and valued. Additionally, pets can help reduce stress and anxiety by providing a calming presence and encouraging physical activity through walking and playing. There is also evidence to suggest that interacting with pets can increase levels of the hormone oxytocin in the brain, which can promote feelings of happiness and well-being. Some research has also suggested that pets may help improve overall mental health outcomes, including reducing symptoms of depression and anxiety.

  It is important to note that while pets can be a valuable source of support and companionship for people with depression, they should not be viewed as a replacement for professional treatment. It is essential to seek help from a mental health professional if you are struggling with depression and to continue to prioritize self-care and other healthy coping mechanisms in addition to any benefits provided by a pet.

- **Has Park:**

  Yes, spending time in nature, including parks, can help reduce the symptoms of depression in some people. Studies have shown that exposure to green spaces, such as parks and forests, can improve mood, reduce stress and anxiety, and even improve cognitive functioning. One reason for this may be that being in nature helps reduce feelings of isolation and provides opportunities for social interaction and physical activity. Additionally, being in the presence of greenery and other natural beauty can help people feel calm and relaxed, which can be especially helpful for those who are depressed.

In addition, spending time in parks can provide a sense of escape from the pressures and demands of daily life, allowing people to take a break from the stressors that may be contributing to their depression. Overall, while spending time in a park may not be a cure for depression, it can be a helpful tool for managing symptoms and improving overall mental health and well-being.

- **Is high social media usage:**

  High social media usage during depression can be a common behavior, but it is not necessarily a healthy coping mechanism. While social media can provide a sense of connection and community, it can also exacerbate feelings of loneliness, anxiety, and depression, especially if the content being consumed is negative or triggering. One reason people may turn to social media during depression is to seek validation and support from others. However, social media interactions are often superficial and lack the depth and intimacy needed for genuine connection and support.

  Additionally, social media can be a source of comparison and self-doubt, which can contribute to negative self-esteem and exacerbate symptoms of depression. The constant bombardment of curated and idealized images and lifestyles on social media can create unrealistic expectations and a feeling of inadequacy. It is important for individuals with depression to be mindful of their social media usage and to seek out healthy coping mechanisms, such as seeking professional help, practicing self-care, and engaging in activities that bring joy and meaning. Social media can be a useful tool for connecting with others and finding information and support, but it should not be relied upon as the sole source of validation or as a substitute for professional help.

- **Is flexible hours:**

> Flexible working hours can help reduce the symptoms of depression for some people. One of the challenges of living with depression is maintaining a healthy work-life balance, and flexible working hours can provide individuals with the opportunity to manage their work schedules to better accommodate their mental health needs. Having the ability to adjust work hours can help individuals with depression better manage their symptoms by allowing them to schedule appointments and attend therapy sessions, take time off for self-care, and incorporate activities that promote their mental well-being into their daily routines.
>
> Flexible working hours can also help reduce stress and increase job satisfaction, which can have a positive impact on overall mental health. By allowing individuals to better manage their workload, they may feel less overwhelmed and more in control of their work, which can reduce the impact of work-related stress on their mental health. However, it is important to note that flexible working hours alone may not be enough to alleviate symptoms of depression. Individuals with depression need to seek professional help and engage in healthy coping mechanisms, such as exercise, mindfulness, and social support. Additionally, workplace support and accommodations, such as counseling services or the option to work remotely, can also be beneficial for individuals with depression.

The questionnaire was created in both English and the language that the respondents spoke, with the respondents' levels of education being taken into mind when doing so. The data that was collected has been put to use to conduct research into the major factors that contribute to depression in individuals. The survey is based on the responses to these 21 behavioural questions as well as 4 positive questions, a weekly survey of an individual, and certain personal particulars such as age group, gender, qualification, occupation, annual income, marriage status, and residence status. In addition, the survey takes into account a weekly survey of an individual. This survey is now being distributed throughout campus as well as among close friends and family members. With the assistance of this survey, we were able to compile a total of 1694 records.

Qs.	Description	Question Response			
1	Are you Losing interest in social activities?	Yes	No	Sometimes	NA
2	Are you facing the loss of Energy or excessive tiredness?	Yes	No	Sometimes	NA
3	Are you losing excitement in activities those used to excite earlier?	Yes	No	Sometimes	NA
4	Do you prefer to sit alone?	Yes	No	Sometimes	NA
5	Are you less interactive as per people's point of view?	Yes	No	Sometimes	NA
6	Do you persistently feel the sadness of mood?	Yes	No	Sometimes	NA
7	Do you often notice having frequent crying spells?	Yes	No	Sometimes	NA
8	Do you feel less Confident?	Yes	No	Sometimes	NA
9	Are you facing difficulties in planning and executing tasks?	Yes	No	Sometimes	NA
10	Have you become indecisive?	Yes	No	Sometimes	NA
11	Are you facing concentration issues?	Yes	No	Sometimes	NA
12	Are you persistently feeling of self-worthlessness?	Yes	No	Sometimes	NA
13	Are you feeling of empty and emotional numbing?	Yes	No	Sometimes	NA
14	Are you feeling of hopelessness?	Yes	No	Sometimes	NA
15	Do you feel that nobody understands you?	Yes	No	Sometimes	NA
16	Do you have sleeping disturbance?	Yes	No	Sometimes	NA
17	Are you feeling changes in appetite and significant weight lose?	Yes	No	Sometimes	NA
18	Are you feeling often restless or being slowed?	Yes	No	Sometimes	NA
19	Do you have ever thought of attempting suicide (Deliberate self-harm/death wishes/ ideation / made plans / attempted)?	Yes	No	Sometimes	NA
20	Do you think these symptoms are present persistently for more than two weeks?	Yes	No	Sometimes	NA
21	Do you feel these symptoms put a significant impact on your Social / Occupational /Family or other important areas of your life?	Yes	No	Sometimes	NA
22	Do you have Pets at home?	Yes	No	-	-
23	Do you have a park nearby your house?	Yes	No	-	-
24	Do you have high social media usage?	Yes	No	-	-
25	Do you have flexible hours?	Yes	No	-	-

TABLE 3.1: *Survey Description*

Daily Sentiment Report (To record day wise sentiments, from Monday to Sunday)						
Lonely	Sad	Not Happy	Feel Nothing	Neutral	Happy	Very Happy

TABLE 3.2: *Weekly Survey (in addition to 25 questions)*

In light of the many challenges that must be surmounted to diagnose depression, we have developed a support system called the Depression Check Tool. This tool assists individuals in determining their mental level and was done so in light of the numerous obstacles that must be surmounted to diagnose depression. Python is the name of the programming language that was utilized by our team to put this concept into action. The machine learning algorithms are the ones who are in charge of putting the methodical procedures into action, which are necessary to build the information management system. The discipline of machine learning can be subdivided into many different subfields, some of which are linear regression, instance-based modeling, clustering, decision trees, and a large number of other subfields. We have developed a model that makes use of the K-Nearest Neighbour, which, when applied to specific questions, will produce the most accurate response conceivable. KNN is most useful in situations in which obtaining labeled data is either impractical or impossible, and it is capable of achieving a high level of accuracy in a wide variety of prediction-type issues. KNN is also useful in situations in which there is a lack of consistency in the data that is being used to make the predictions.

The facts gathered and the findings reached by 1694 people hailing from a variety of geographic areas are presented in the first section of this article. The questions that were asked of these people were based on several different criteria. The findings of this research study will be helpful in the development and use of diagnostic criteria that can be applied to mental illness. The machine learning algorithms are the ones who are in charge of putting the methodical procedures into action, which are necessary to build the information management system.

The first phase in the process of developing our model is the collection of data, and the second step is the implementation of the framework. During the first section,

Objective	**Description**	**Instrument/Tool/ sample design etc. to be used**
1	**1694** **Sample size (No. of participants)**	Primary data collection, Google form
2	Depression Check Tool framework	a. HTML Language b. CSS Language c. Python 3.7 d. Machine Learning e. Flask
3	Depression Check Tool website	

Table 3.3: *Methodology/Tools/Instruments to be used*

we gathered data on determining the participants' mental health from a total of almost 1,694 people residing in a wide variety of locales. When it is finished, several distinct algorithms will be compared to previously established ways, and the positive impact that they will have on society will also be discussed. We have developed an efficient framework for estimating the level of depression that will be used in the second part of the procedure by making use of these data. This framework will be used in the second part of the operation. We have also developed a website that will be of use to the community as a whole, which is in addition to the previous point.

3.2 Machine learning workflow

To make a correct diagnosis of mental illness and be better able to assist farmers in resolving the issues that have been highlighted here, our team has developed a system that is referred to as the Depression Check Tool. The framework illustrates the behavioral inquiries, in addition to specific particulars of the people and some positive queries based on human life. It is the responsibility of each participant to provide their responses to these questions and then click the submit button. The code for this website was written with the Python programming language, and the HTML and CSS that were used to construct it were created with the assistance of Flask.(see table 3.3).

When assessing a person's level of depression, we compared the findings with three distinct algorithms: Naive Bayes, Decision Tree, and KNN. Each algorithm was designed to predict depression severity. These techniques are applied to evaluate the reliability of the findings. We have divided the dataset in half, and for each portion, we have crafted a training data set as well as a test data set. Seventy percent of the data is utilized in the process of training the model, and thirty percent of the data is utilized in the process of testing the correctness of the model utilizing the data from the trained model.

In the proposed methodology (see Figure 3.2), In the first stages of the process

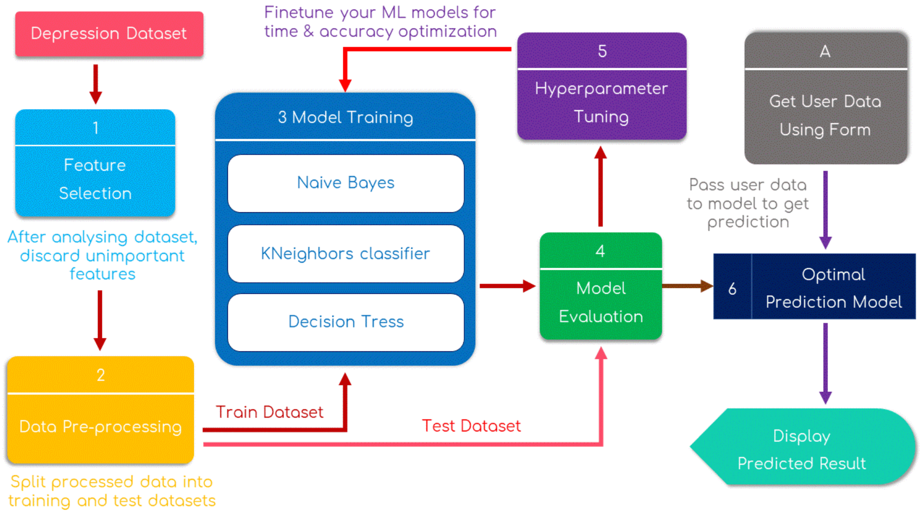


FIGURE 3.2: *Workflow of proposed methodology.*

of compiling data, surveys are the primary method of data collection. This survey includes several questions, the formulation of which was accomplished with the assistance of a psychiatrist. After the data for the dataset have been collected, the data will be analyzed, and any aspects of the dataset that are deemed to be insignificant will be eliminated at this stage. The following step, which comes after the phase in which it is decided which features will be utilized, is to preprocess the data in any way that may be required. It is not viable to incorporate data from the real world directly into machine learning models since the settings under which these data are collected do not conform to ideal conditions. Data collected from the real world often contains noise, is missing numbers, and even has an incorrect format. It is required to carry out the activities that are collectively referred to as data pre-processing to clean the data and organize it in a manner that is suitable for a machine learning model. This is because the data cannot be used until it has been properly prepared. Because of this, the data will be able to be utilized properly. (see Figure 3.3),

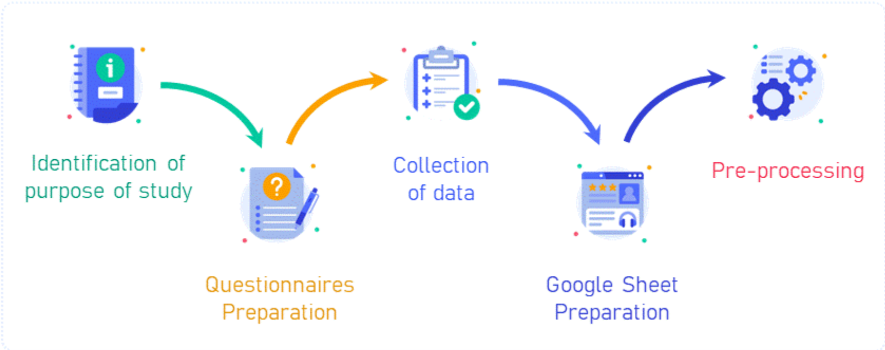


FIGURE 3.3: *Data pre-processing steps.*

As a consequence of this, the machine learning model will have a higher level of both accuracy and efficiency going forward. In addition, once the dataset has been processed, it is then split into two parts: the test dataset and the training dataset. After that, three distinct models of machine learning are contrasted with one another to establish which of the models is superior in terms of precision and effectiveness. Our model's hyperparameters are also optimized for optimal performance in terms of both accuracy and the amount of time it takes to run. As a result of researching the model that was suggested, we have designed a website specifically for the users, and in the not-too-distant future, we will be able to collect the dataset with the use of that website. To respond to the questions that are presented on this website, a person has to fill out a form first. This is a requirement. After all of the fields have been filled in, the user must click the "submit" button before the form is considered complete. In addition to this, the model can evaluate a person's general level of depression. The website in question makes use of the suggested algorithm, which plays a part in the generation of results of higher general quality. (see Figure 3.4).

3.3 Proposed algorithm

The proposed algorithm used to identify the depression level is as follows:

1. Open web-app

2. Fill Details:

- **2.1.** Enter: personal details
- **2.2.** Answer: lifestyle questions
- **2.3.** Answer: behavioural questions
- **2.4.** Enter: 7-day sentiment records
- **2.5.** Submit Form

3. Prepare data by scaling, missing value treatment, and dimensionality reduction as required.

4. Provide prepared data to model

5. Predict a class value for new data:

- **5.1.** Calculate distance (X, Xi) from i=1,2,3,….,n. where X= new data point, Xi= training data, and distance as per your chosen distance metric (euclidian distance in our case)

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

- **5.2.** Sort these distances in increasing order with corresponding train data.
- **5.3.** From this sorted list, select the top 'K' rows.
- **5.4.** Find the most frequent class from these chosen 'K' rows. This will be your predicted class.

6. Set depression level as per predicted class

- **6.1.** If the predicted class is 1: then depression level -> mild
- **6.2.** If the predicted class is 2: then depression level -> moderate
- **6.3.** If the predicted class is 3: then depression level -> severe

7. Return: depression level

FIGURE 3.4: *Algorithm to identify the depression level in the proposed methodology.*

3.4 Depression tool - website

Our group has not only developed K-Nearest Neighbour for the sake of this investigation, but we have also created a website that is referred to as the Depression Check Tool. Users of this website can, in a relatively short period, acquire an accurate diagnosis of the level of depression they are currently experiencing in their lives. The development of a diagnostic instrument for depression is the third goal that we hope to accomplish with the study that we are currently carrying out. There is access to three tabs on this page; the ones that are active right now are titled Home, Our Model, and Traditional Model. The proposed model snapshots are attached here. (see Figure 3.5, Figure 3.6, Figure 3.7, Figure 3.8).

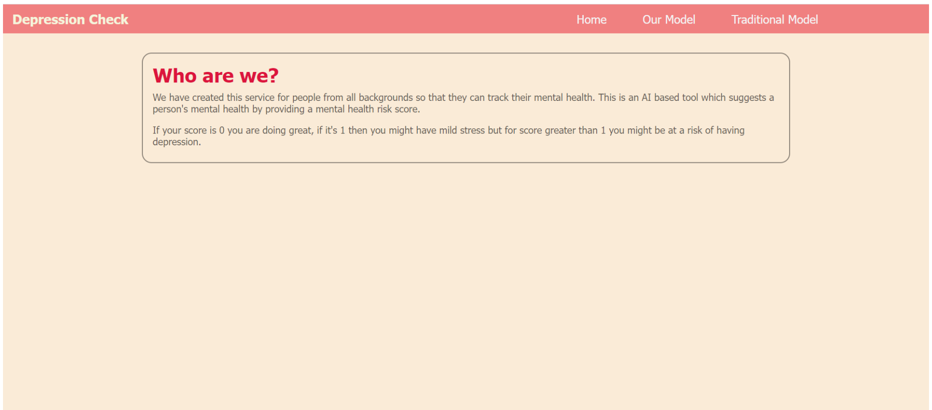


FIGURE 3.5: *Home page of proposed system - website.*

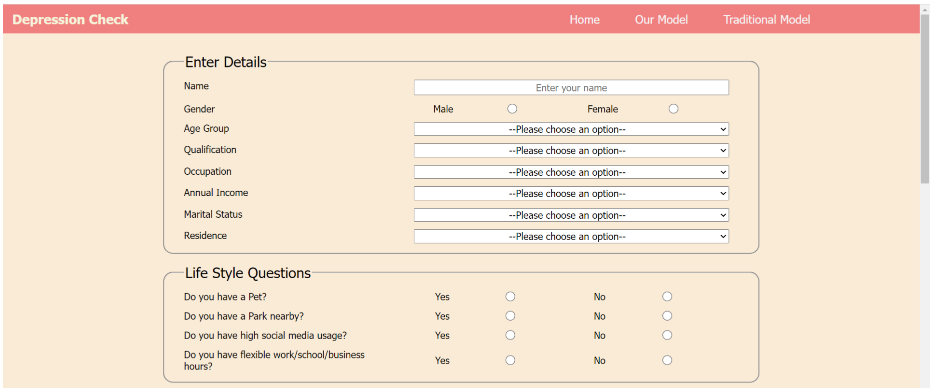


FIGURE 3.6: *Depression check tool – proposed model – page 1.*

3.5 Summary

This chapter provides a suggestion for an intelligent system, one component of which is the production of a website that can assess a person's level of depression. Another component of this chapter's proposal is the establishment of a website that can assess a person's level of anxiety. We performed research and gathered data from a total of 1694 people from a wide range of locales to achieve the first of our goals. To construct a system that asks users for their responses to a survey that contains

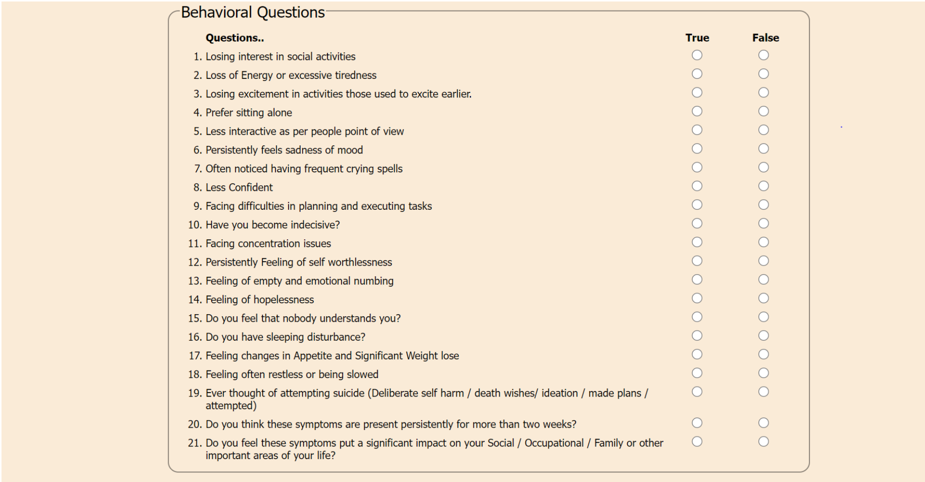


FIGURE 3.7: *Depression check tool – proposed model – page 2.*

FIGURE 3.8: *Depression check tool – proposed model – page 3.*

a variety of different kinds of questions to fulfill the second objective, a technique from the field of machine learning known as K-Nearest Neighbour was applied. This allowed for the successful construction of the system. The development of a model that is capable of reliably predicting the level of depression a person is experiencing based on the responses they provide to our questions is the third objective we have set for ourselves. Comparing and analyzing our model with a wide variety of other machine learning classifiers is one of the steps we take toward achieving the fourth objective. This illustrates that, according to the dataset that we used, KNN delivers results and accuracy that are superior.

CHAPTER 4

Results and discussions

The findings and subsequent discussion regarding the diagnosis of depression using various machine learning algorithms are presented in this chapter. The information of 1694 different people was acquired for this article, and then that information, together with the other information gathered, was examined. For the goal of doing meaningful data analysis, a hybrid method has been developed; this method may also be used in the future as the technological answer to the question of how to diagnose depression. To carry out the analysis of the gathered samples, machine learning techniques were utilized. The investigation makes use of three distinct classification strategies derived from machine learning: a decision tree, a Naive Bayes classifier, and a K-Neighbours classifier. To get the most precise forecasts possible, the classifiers that were selected are put to work. This chapter presents the findings, which show what percentage of the general population suffers from depression. It was important to extract a vast amount of information from the dataset to generate reliable forecasts. The source of this information was the dataset. Based on the datasets that have been collected, a website has been developed that enables users to check their mental condition or to see what kind of assessment may be made regarding the individual's level of depression [126].

The research that has been done is being carried out to bring about additional developments in the area of psychiatry. In today's modern society, there has been a discernible rise in the likelihood that an individual may experience a depressive episode. The reason behind this is discussed under the following headings:

- In addition to other symptoms, depression is characterized by a loss of energy, difficulties concentrating, interrupted sleep, altered appetite, irritability, and mood swings. These causes are primarily responsible for the condition. The variations in mood swings that people experience from one another are based on a variety of different factors that commonly cause depression.

- The aforementioned issues are to blame for the presence of depression in people's lives, and they may be traced back to the origin of the condition. A survey was conducted based on various parameters, and the application of technical solutions was carried out to identify whether or not a person was suffering from depression. To take this into consideration, the survey was carried out.

- It has been concluded, following an examination of the pertinent research, that there are a variety of approaches and assessments that can be applied in the process of making a clinical diagnosis of depression. In the process of assessing whether or not a person suffers from depression, a variety of methodologies, including machine learning, lexicon-based analysis, supervised learning, unsupervised learning, and deep learning techniques, among others, are being applied. Texts, images, movies, emoticons, and other digital media along these lines are used to formulate the plan of action.

- After investigating each of these research approaches, it was discovered that the vast majority of the studies are predicated on instruments and questionnaires. These evaluations and questionnaires take into account the problematic aspects of a person's life when providing a diagnosis of depression. Throughout our analysis, we came up with the concept of combining weekly surveys meant to screen for signs of depression with inquiries about the positive aspects of people's lives. This was an idea that we came up with as part of our research.

4.1 Basic dataset collection

To apply the methods of machine learning to the survey dataset, 21 questions that contained personal information were rewarded with the replies yes, no, sometimes, and not relevant added to the list of options. The majority of psychiatrists make use of a scale called the Hamilton Rating Scale, which has been incorporated into a questionnaire that has been developed to gain insight into the mental health of individuals. This questionnaire contains 21 questions, as well as personal details, and uses this scale. The poll provided a total of 1694 papers for our review, bringing the total number of documents to 1694. Questions concerning a person's age, gender, qualification, occupation, annual income, marital status, residence, whether or not they have a pet, how often they use social media, and other personal and professional facts are among the characteristics that are asked about in surveys. To determine whether or not an individual is experiencing depression, a cutoff point is determined; this number can vary anywhere from 0 to 21 (score). However, if the score that is calculated for the individual is between 7 and 14, then the individual is considered to have mild depression. If the score that is acquired for the individual is between 0 and 6, then the individual does not have depression. If the person has a score that falls between 15 and 20, it suggests that they have a moderate case of depression. If the person's score is 21, it suggests that they are suffering from severe depression. The ages of seven, fifteen, and twenty-one are the cutoff points that are most frequently utilized in the process of making a diagnosis of depression. (see table 4.1).

After compiling the results of the questionnaire's responses, the next step involves the addition of four questions that focus on the positive. These questions may involve investigating whether or not an individual makes use of social media and ascertaining whether or not a park is located near their place of residence. After the

Question Description	Response [%]			
	Yes	**No**	**Sometimes**	**NA**
Are you losing interest in social activities?	21	27	51.9	-
Are you facing loss of Energy or excessive tiredness?	30	24	45.4	-
Are you losing excitement in activities those used to excite earlier?	23	26	51	-
Are you prefer to sit alone?	23	25	51.3	-
Are you less interactive as per people's point of view?	38	62	-	-
Do you persistently feels sadness of mood?	37	64	-	-
Do you often noticed having frequent crying spells?	39	39	23.1	-
Do you feel less confident?	64	40	-	-
Are you facing difficulties in planning and executing tasks?	52	32	15.8	-
Have you become indecisive?	55	45	-	-
Are you facing concentration issues?	58	42	-	-
Are you persistently feeling of self-worthlessness?	52	48	-	-
Are you feeling of empty and emotional numbing?	61	40	-	-
Are you feeling of hopelessness?	62	38	-	-
Do you feel that nobody understands you?	60	40	-	-
Do you have sleeping disturbance?	29	55	16.5	-
Are you feeling changes in appetite and significant weight lose?	55	45	-	-
Are you feeling often restless or being slowed?	37	63	-	-
Ever thought of attempting suicide (Deliberate self-harm/death wishes/ ideation / made plans / attempted)?	40	60	-	-
Do you think these symptoms are present persistently for more than two weeks?	40	43	-	17
Do you feel these symptoms put a significant impact on your Social/Occupational/ Family or other important areas of your life?	68	13	-	19

Table 4.1: *Question description with survey response (in %)*

positive questions have been added, there will be a poll of an individual's position on the scale of sentiment conducted over one week. During the research, a cleaned-up version of the data that was generated by carrying out exploratory data analysis (EDA) is gathered and examined. This takes place during the study. In Figure 41, a one-week survey based on a sentimental scale is presented. The individual selected one sentiment from the below scale for one day. For example, if the person selected a negative sentiment, the scale would record a -1 value for that particular day. This process continues for one week, and after that, the average sentiment will be calculated, which is also called feature engineering.

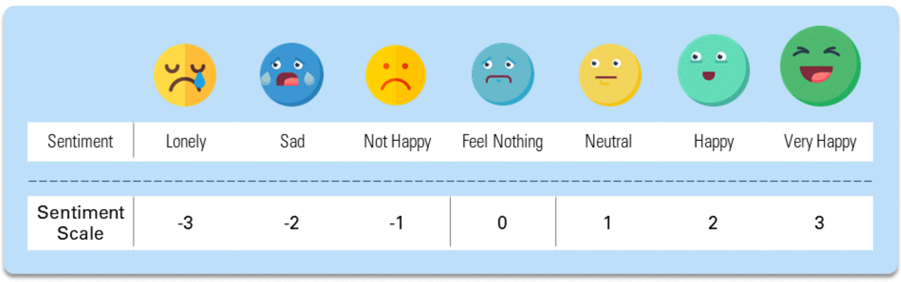


FIGURE 4.1: *Sentiment scale for weekly records.*

Figure 4.2 indicates the level of the score that is appropriate for the various age groups. The survey, which was designed with the assistance of a psychiatrist and contains a total of 21 questions, is centered on cyclical mood changes. The responses that were collected included yes or no. After pre-processing the data, these replies convert into the numbers 1 and 0 accordingly. The favorable response was used as the basis for the aforementioned score evaluation. For instance, if the person responds to the questionnaire, which consists of a total of 21 questions, and out of those questions, 16 questions are answered "yes," then the person has a score of 16. Therefore, this evaluation of the score takes into account a variety of age groups.

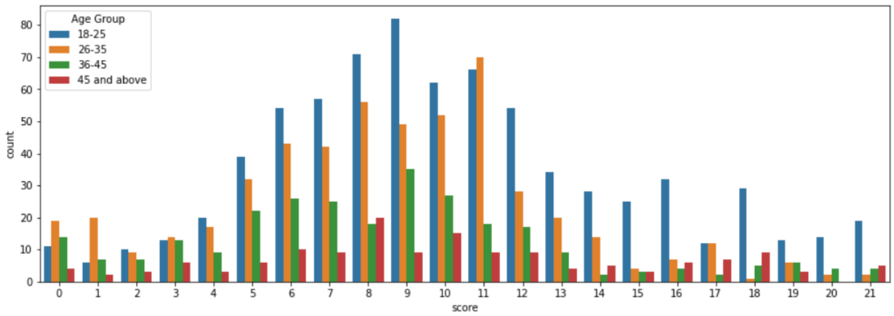


FIGURE 4.2: *Score evaluation based on questions in different age groups.*

4.2 Analysis of dataset

4.2.1 Depression level based on gender

The results of the investigation have been presented in the form of a categorical analysis.Figure 4.3 shows that the majority of males appear to have a depression score between 5 and 12, whereas the majority of females appear to have a more variable score value. When compared to males, there is a 56 percentage increase in the number of females who are recognized as suffering from depression.

4.2.2 Depression on the basis of qualification

Figure 4.4 draws attention to the fact that those who have earned a doctoral degree have a lower risk of suffering from depression compared to individuals who have earned a graduate or postgraduate degree. In addition, the range of depression scores among women who have only a high school education is significantly broader than among women who have earned higher degrees. At the graduate level, females are reporting higher degrees of depression at a rate that is sixty percent higher than that of males.

4.2.3 Depression level depends on annual income

Figure 4.5 displays the level of depression that both males and females experience in relation to annual income. According to one study, women who do not earn an income, such as housewives, appear to have lower levels of stress. In addition, the

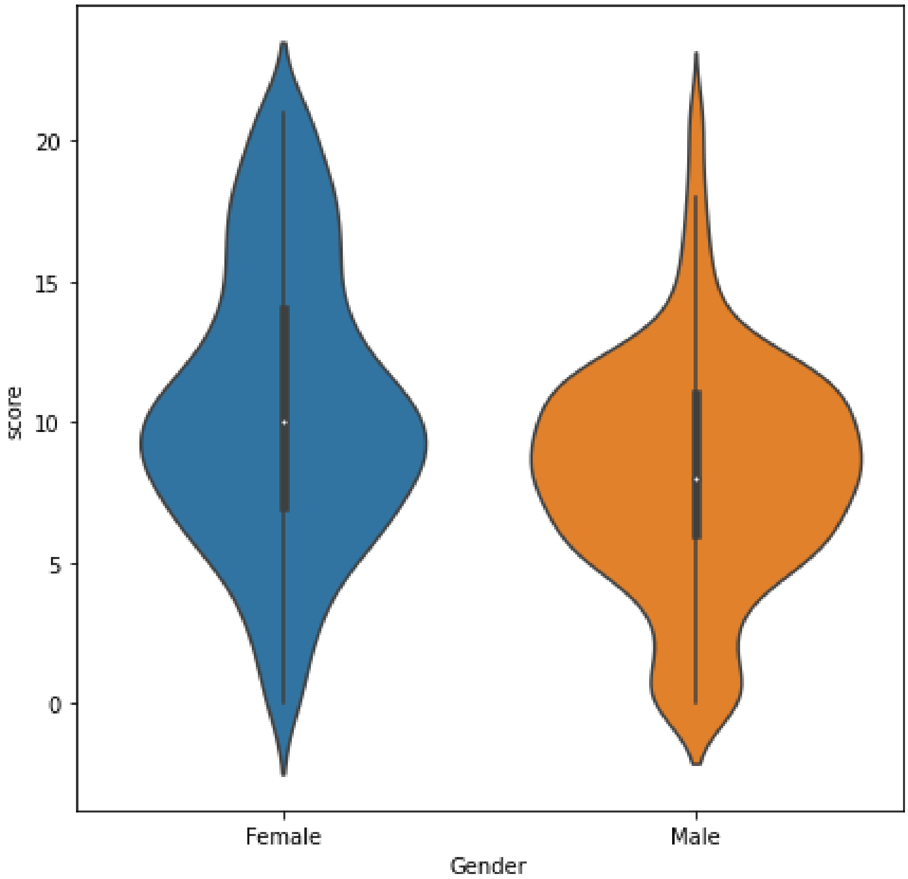


FIGURE 4.3: *Depression level on the basis of gender.*

guys who have a high income (according to the dataset) have lower levels of stress. On the other hand, males who have no income or a low income have the highest levels of depression. When compared to males, it has been discovered that females experience much higher levels of depression.

4.2.4 Depression level on different age groups

Figure 4.6 demonstrates that people between the ages of 18 and 25 are more likely to suffer from depression as a result of difficulties concentrating on tasks. They are worried about both their studies and their prospects in the future. People with an age group older than 45 have a high depression score because they have difficulty organising and carrying out their responsibilities. They are dealing with the stress of their retirement as well as the worry of their children getting married. There are a

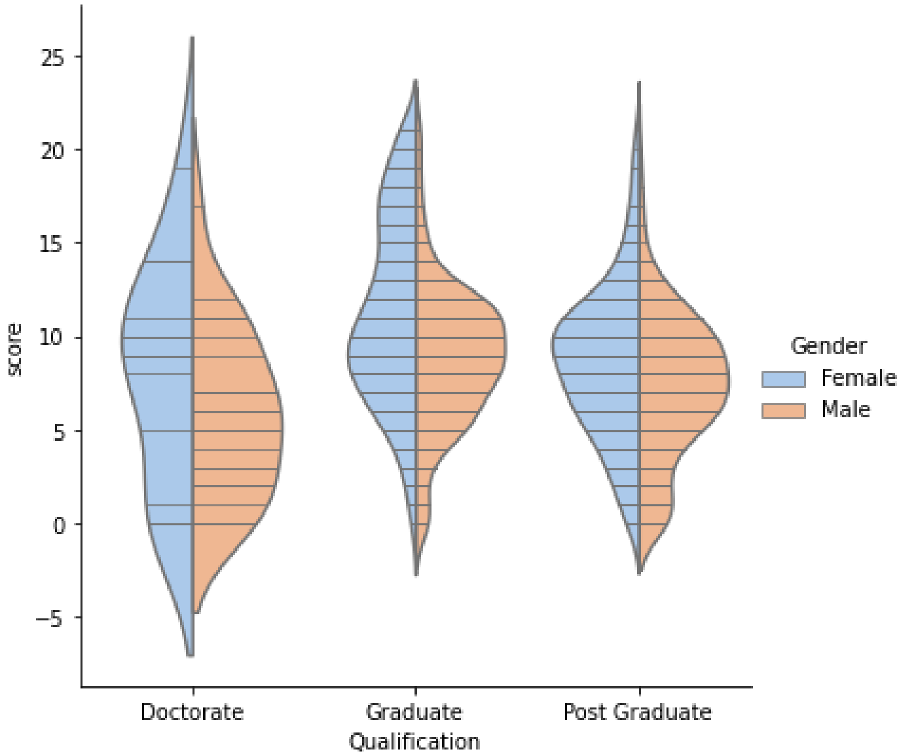


FIGURE 4.4: *Depression on the basis of qualification.*

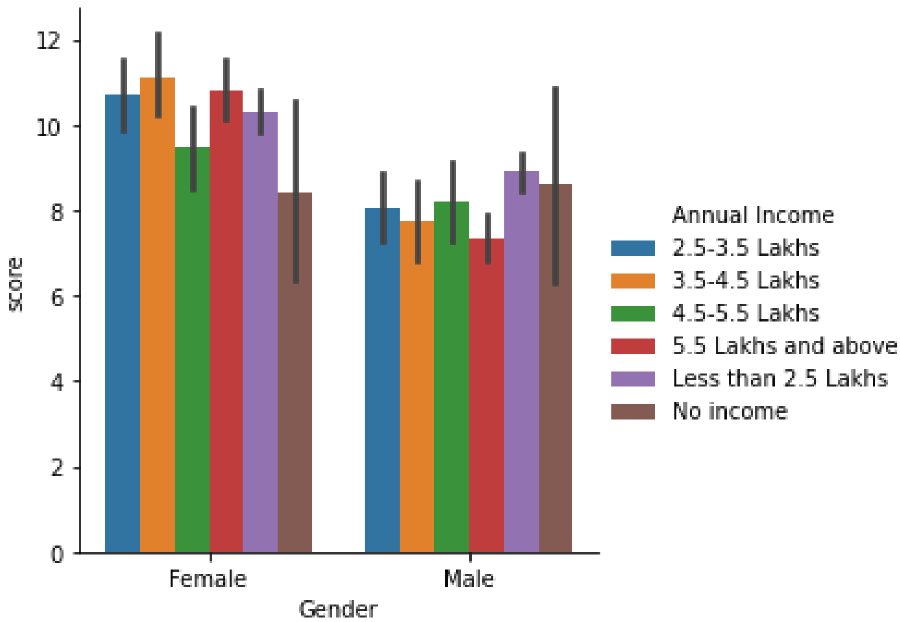


FIGURE 4.5: *Depression level depends on annual income.*

total of 1694 records in the dataset, and we have shown that those between the ages of 18 and 25 and above the age of 45 have an average score that is significantly greater than that of others, indicating a significantly higher level of depression.

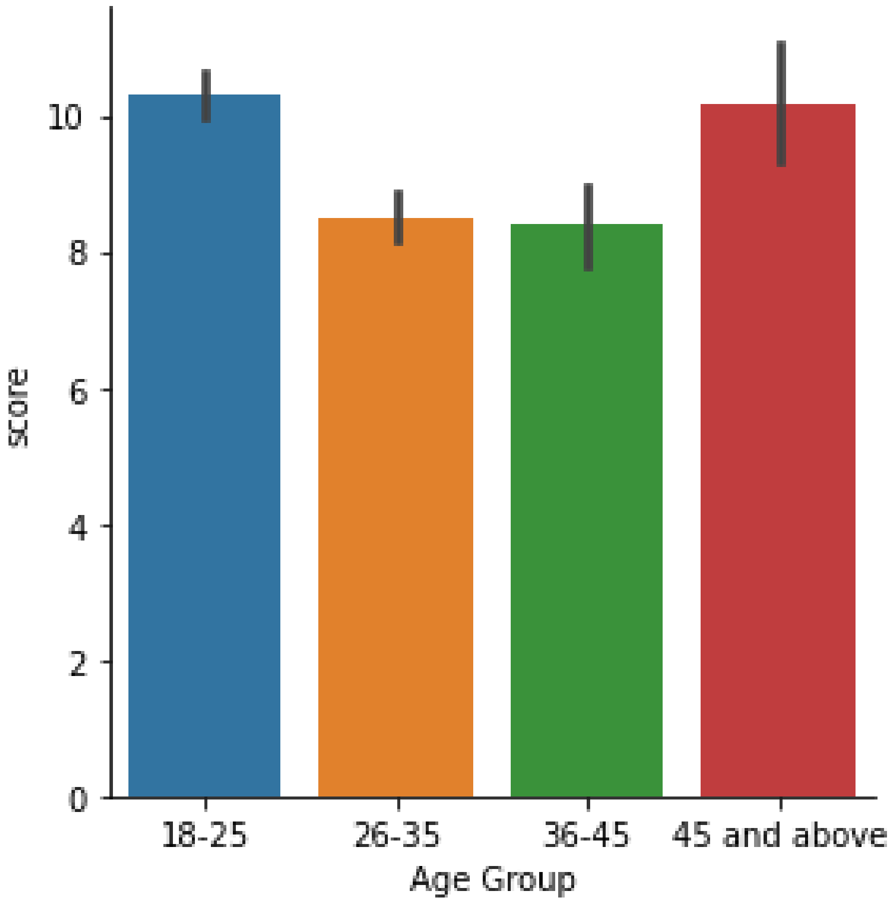


FIGURE 4.6: *Depression level on different age groups.*

4.2.5 Depression level at marital status - age group wise

Figure 4.7indicates that people of a certain age group who are married and experience feelings of indecision and restlessness have a high risk of developing depression because they are burdened with a number of responsibilities in their lives, such as the upkeep of a household, the education of their children, and the satisfaction of their requirements. On the other hand, those of the same age group who aren't married are more likely to be anxious about their academics and their professional prospects in the future. In addition, the persons are over the age of 45 and have suffered from significant levels of depression throughout their lives, regardless of whether or not they are married.

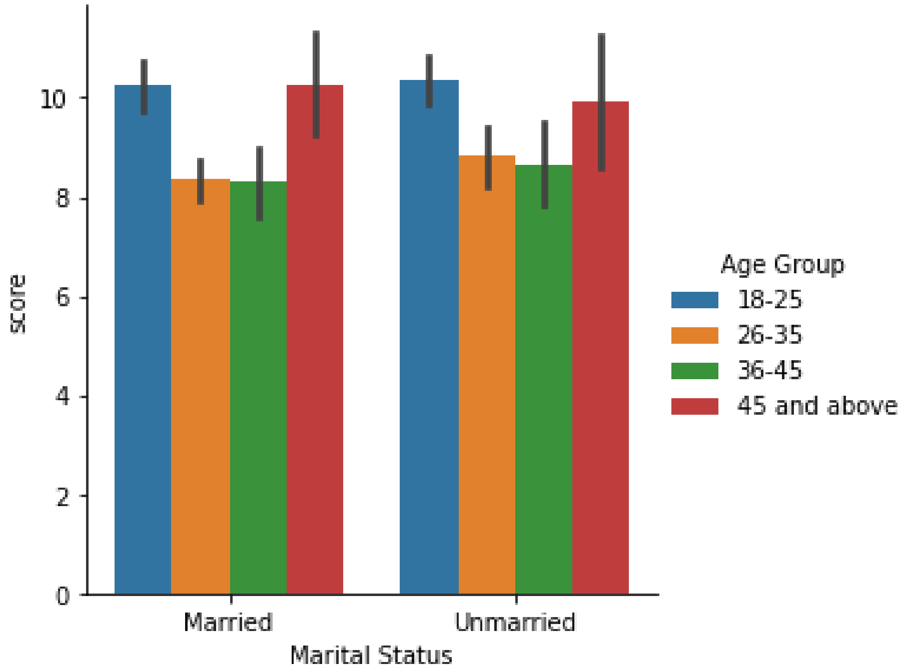


FIGURE 4.7: *Depression level at marital status - age group wise.*

4.2.6 Depression level at residential facilities

Figure 4.8 The residential areas serve as the basis for the analysis. It has been observed that people who live in urban areas seem to have a high depression score because of a loss of energy and excessive tiredness. This is because in as serve as the basis for the analysis. It has been observed that people who live in urban areas seem to have a high depression score because of a loss of energy and excessive tiredness. This is because in cities, people's needs are very high, whether they are married or unmarried. This is the case regardless of whether the person is married or unmarried. However, because the amenities in rural areas are about on par with those in urban areas, the requirements of the local populace are not significantly greater.

4.2.7 Depression level at occupation

Figure 4.9 The degree to which an individual is affected by depression as a result of their employment. The dataset reveals that it has been found that students appear to have more varied values than other people. On the other side, it is acknowledged that females who are in business have greater levels of depression score values than

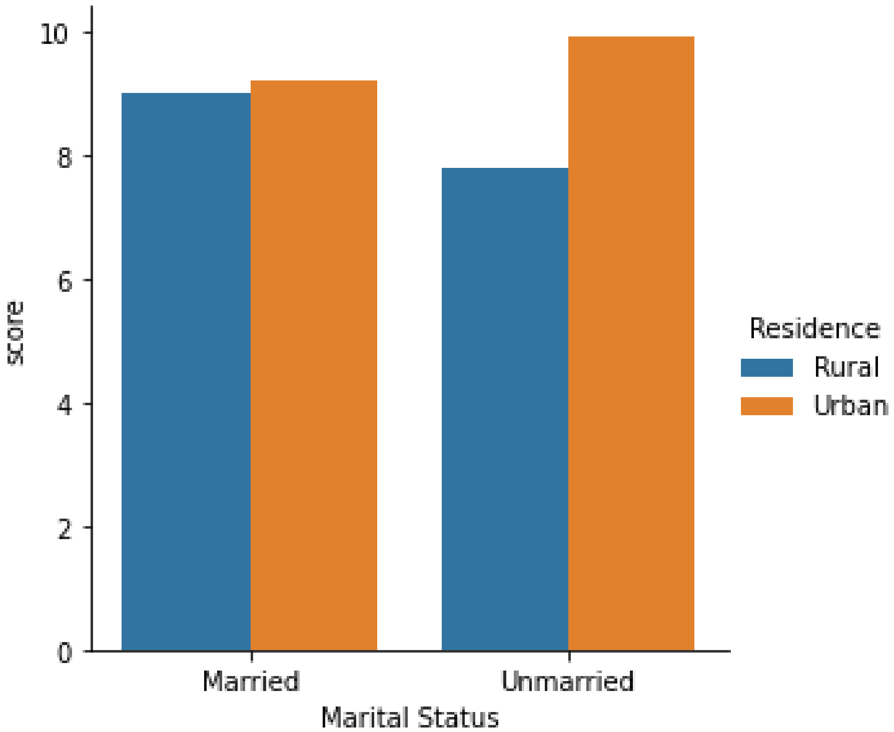


FIGURE 4.8: *Depression level at residential facilities.*

ones who are in employment, and the reason for this is that females have more duties in addition to jobs and businesses.

4.2.8 Depression level at marital status

Figure 4.10 reveals that the severity of depression in males can differ based on their marital status and the type of relationship they have with their partner. Because unmarried men worry more about their careers, employment, and the possibilities for their futures, the rate of depression among single men is substantially higher than that of married men. This is due to the fact that unmarried men have more control over their own destinies. They are anxious about the stability of their lives as well as the amount of money coming into their household.

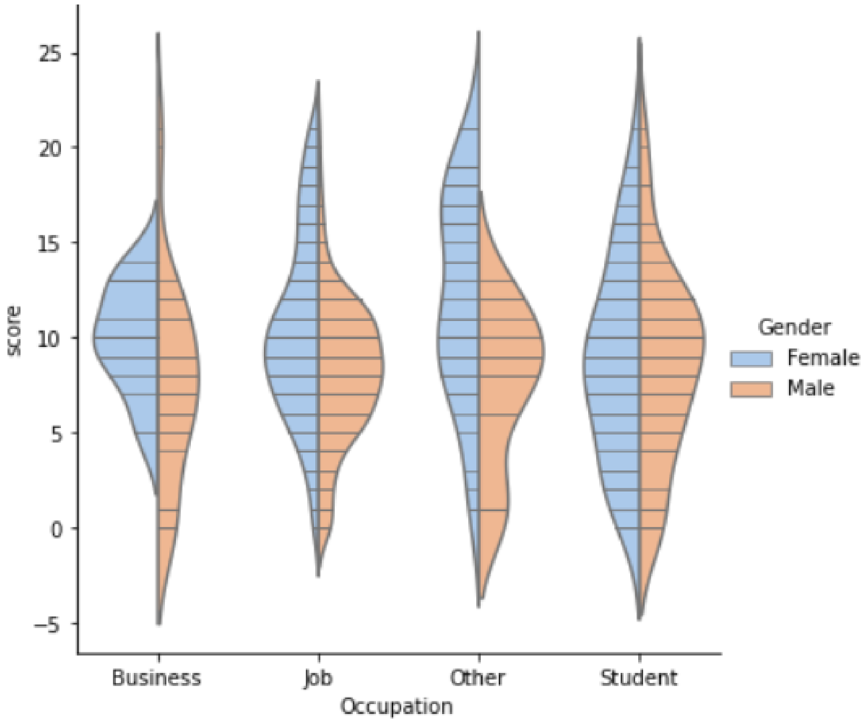


FIGURE 4.9: *Depression level at occupation.*

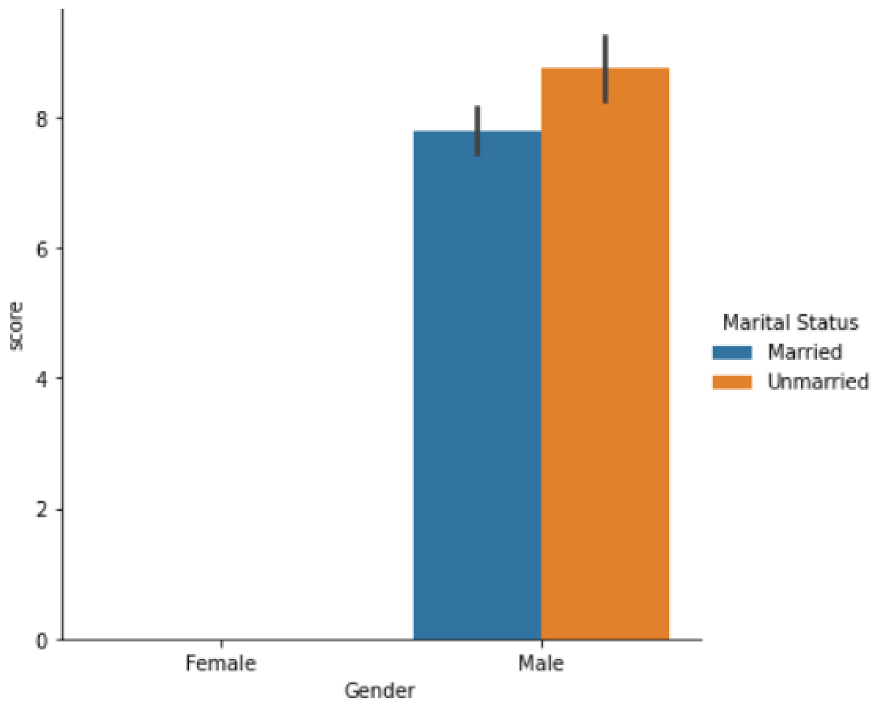


FIGURE 4.10: *Depression level at marital status - gender wise.*

4.3 Comparative analysis of decision tree, knn and naive bayes

In Figure 4.11 (a) According to the study, our model successfully predicted 145 out of 145 individuals with a zero depression level, making the total number of accurate predictions 145. And last, for 0 individuals, our model predicted that they would have a depression level of 1, when in reality, they had a depression level of 0. In the case of depression level 1, our model correctly predicted 282 out of a total of 336 participants who had one depression level (43 + 282 + 11). And for 43 people, our model projected their depression level as 0 when in fact they were at depression level 1, and for 11 people, our model forecasted their depression level as 2, when in fact they were at depression level 1. For depression level 2, our model correctly predicted 67 out of 79 people (67 + 12 + 0), making the total number of people affected by depression level 2 79. And for 12 individuals, our model estimated that they were at a level of depression equal to 1, but in reality, they were at a level of depression equal to 2. In conclusion, the accuracy of the Naive Bayes method is 88.21%. (see Figure 4.12 (d)).

In Figure 4.11 (b) It has been observed that our model correctly predicted 131 out of 145 people who had a depression level of 0; however, for 14 of those people, our model incorrectly predicted that they had a depression level of 1, when in reality, they had a depression level of 0. This phenomenon was observed for depression levels 0 and 1. In the case of depression level 1, our model correctly predicted 303 out of a total of 336 individuals with one depression level (20 + 303 + 13). And for 20 people, our model projected their depression level as 0 when in fact they were at depression level 1, and for 13 people, our model forecasted their depression level as 2, when in fact they were at depression level 1. For depression level 2, out of 79 people (1 + 10 + 68), our model predicted 68 accurately. And for 10 participants, our model predicted a depression level of 1, while in actuality they were at depression level 2. Finally, the accuracy of the decision tree is 89.64%. (see Figure 4.12 (e)).

In Figure 4.11 (c) This confusion matrix demonstrates that for depression level 0, our model successfully predicted 136 out of a total of (136 + 9) 145 individuals with zero depression level. And for nine individuals, our model estimated that they had a level of depression equal to 1, when in reality they had a degree of depression equal to 0. For those with depression level 1, our model correctly predicted 307 out of a total of 336 people with one depression level (11 plus 307 + 18). And for 11 individuals, our model estimated that they were at a level of depression equal to zero, when in reality, they were at a level of depression equal to one. Rest for eighteen individuals; our model had projected that they would have a depression level of two, but in reality, they had a depression level of one. For those with depression level 2, our model correctly predicted 74 out of a total of 79 people who had that level of depression (0 + 5 + 74). And for five individuals, our model projected that they would have a depression level of one, when in reality, they had a depression level of two. In conclusion, KNN has an accuracy of 92.32%. (see Figure 4.12 (f)).

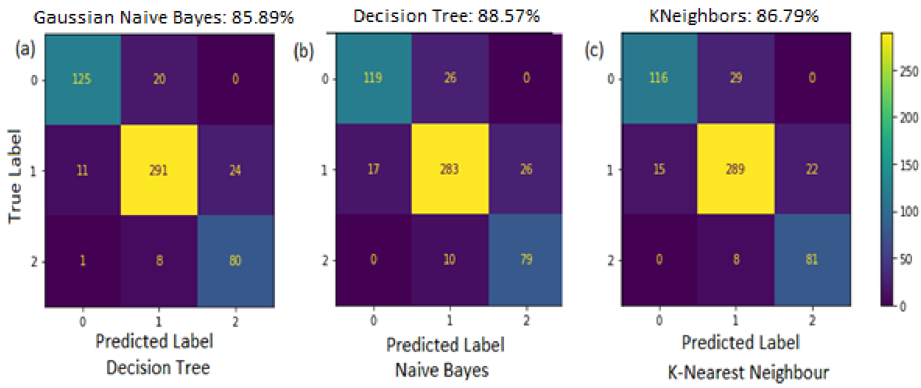


FIGURE 4.11: *Confusion matrix of Decision tree, Naïve Bayes and KNN (a-c) (before improvement).*

On the basis of the results of the aforementioned questionnaire survey, a comparative analysis was performed first on three different machine learning models, namely decision tree, naive bayes, and KNN models. It has been noted that the accuracy of the decision tree is 88.5%, while the accuracy of naive bayes is 85.8%, and the accuracy of KNN is 86.7%. After then, the improvement was made and a new model was offered, both of which are described in the data description. This new model includes both the weekly survey of an individual as well as the addition of positive

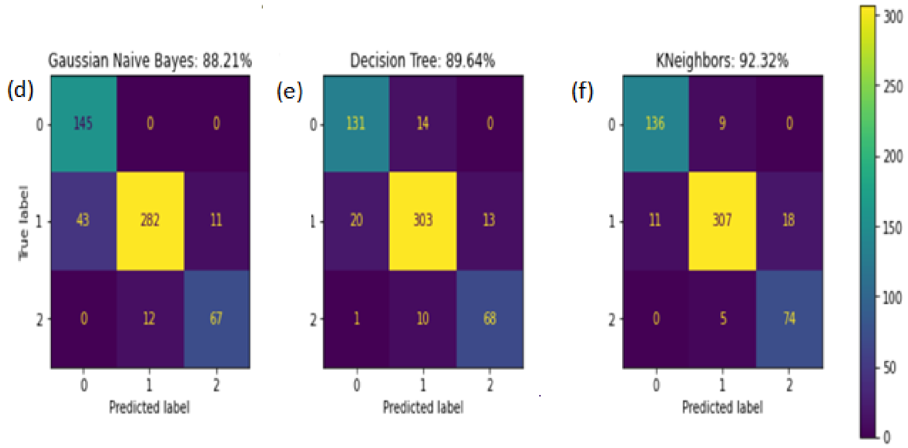


FIGURE 4.12: *Confusion matrix of Decision tree, Naïve Bayes and KNN (d-f) (after improvement).*

questions. Following the comparison of the confusion matrix comes the comparison of actual data vs anticipated data in the form of a plot. (see Figure 4.13)

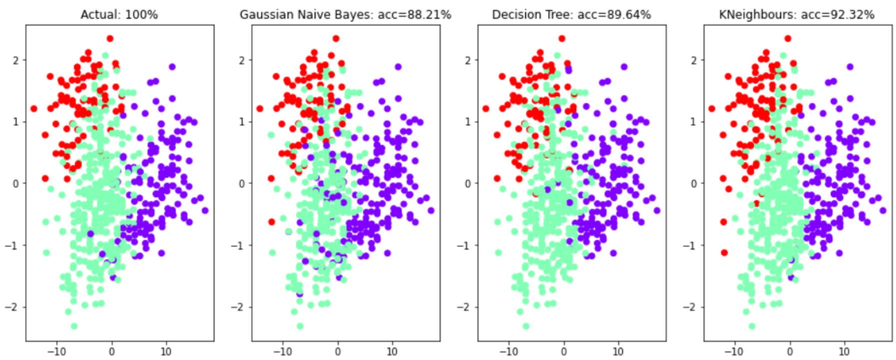


FIGURE 4.13: *Comparison of actual values and predicted values.*

CHAPTER 5

Conclusion and future scope

5.1 Thesis summary

This chapter includes a summary of the work accomplished in the thesis and the future perspective of the work. The first objective of this work was to survey people to detect depression. Herein, 1694 people were surveyed from different areas. The issues were also examined and explored from different parameters, namely, education level, marital status, age groups, residential areas, and occupation level of an individual. Earlier, depression was identified through face-to-face interaction with the psychiatrist. However, there is a lack of awareness about the level of depression. Most of the time, depression is identified at a severe level. The severity of depression mostly leads to suicide. To address these critical issues, the present study has developed a framework named "Depression Check Tool," in which the depression level can be identified with the help of a questionnaire. The study has also developed the concept of a machine-learning model in the system. The study finds that the KNN is the best technique in machine learning. In addition, the Depression Check Tool aims to improve the quality and efficiency of detecting depression at an early stage. The main focus of this thesis is to identify the depression level of an individual. The Naive Bayes model, the K-Nearest Neighbour model, and the Decision Tree model were the three models concentrated in the work. These three are completely unrelated to one another. Compared to the results of the current models, the suggested model's findings are more accurate. The work is completed with the help of machine learning techniques to create a website that can assess a person's mental capabilities.

5.2 Conclusion

In the second chapter, conducted a review of the literature, which resulted in the production of many unique concepts and the discovery of a market need for a questionnaire-based depression screening tool. The examination of methodology in the third chapter provides specifics on how we put the earlier principles into practice. The fourth chapter is devoted to going over the conclusions and judgments made. In the literature review, we have searched out several surveys and tools that are already working to detect depression. However, these surveys and questionnaires are based on negative questions, in which all the questions are related to negative aspects and thoughts of life. According to the second objective, one questionnaire has been prepared in which negative and positive questions are added along with the one-week survey of an individual. After the collection of records, the data was pre-processed. That pre-processed dataset was used in different types of three models, such as Nave Bayes, Decision Tree, and K-Nearest Neighbour. After training and evaluating various models on our training and testing dataset, we found that KNN performed best on our dataset with much accuracy.

5.3 Future research directions

To identify the depression level of a person, an internet-based mobile application has been developed. It means depression can be easily identified at an early stage. Furthermore, the developed model shall be modified as per the real dataset created in the upcoming times. In the concluding note, it is worth mentioning that the problem presented in this thesis is beneficial for society. This kind of research is thus very helpful for psychiatrists and their patients.

BIBLIOGRAPHY

[1] Indranil Chakraborty and Prasenjit Maity. Covid-19 outbreak: Migration, effects on society, global environment and prevention. *Science of the Total Environment*, 728:138882, 2020.

[2] F Binti Hamzah, C Lau, Hafeez Nazri, Dominic Vincent Ligot, Guanhua Lee, Cheng Liang Tan, MKBM Shaib, Ummi Hasanah Binti Zaidon, Adina Binti Abdullah, Ming Hong Chung, et al. Coronatracker: worldwide covid-19 outbreak data analysis and prediction. *Bull World Health Organ*, 1(32):1–32, 2020.

[3] Ashok Kumar Verma and Sadguru Prakash. Impact of covid-19 on environment and society. *Journal of Global Biosciences*, 9(5):7352–7363, 2020.

[4] S Mahendra Dev, Rajeswari Sengupta, et al. Covid-19: Impact on the indian economy. *Indira Gandhi Institute of Development Research, Mumbai April*, 2020.

[5] Shazia Rashid and Sunishtha Singh Yadav. Impact of covid-19 pandemic on higher education and research. *Indian Journal of Human Development*, 14(2): 340–343, 2020.

[6] Sofia Arora and Arun Malik. A systematic review on sentiment analysis for the depression detection during covid-19 pandemic. In *2022 10th International*

Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), pages 1–6. IEEE, 2022.

[7] Sumitra Pokhrel and Roshan Chhetri. A literature review on impact of covid-19 pandemic on teaching and learning. *Higher Education for the Future*, 8(1): 133–141, 2021.

[8] Purude Vaishali Narayanrao and P Lalitha Surya Kumari. Analysis of machine learning algorithms for predicting depression. In *2020 international conference on computer science, engineering and applications (iccsea)*, pages 1–4. IEEE, 2020.

[9] Yalin Baştanlar and Mustafa Özuysal. Introduction to machine learning. *miR-Nomics: MicroRNA biology and computational analysis*, pages 105–128, 2014.

[10] Osvaldo Simeone. A very brief introduction to machine learning with applications to communication systems. *IEEE Transactions on Cognitive Communications and Networking*, 4(4):648–664, 2018.

[11] Wei Zhang and Feng Gao. An improvement to naive bayes for text classification. *Procedia Engineering*, 15:2160–2164, 2011.

[12] Ashis Pradhan. Support vector machine-a survey. *International Journal of Emerging Technology and Advanced Engineering*, 2(8):82–85, 2012.

[13] Yan-Yan Song and LU Ying. Decision tree methods: applications for classification and prediction. *Shanghai archives of psychiatry*, 27(2):130, 2015.

[14] Zhongheng Zhang. Introduction to machine learning: k-nearest neighbors. *Annals of translational medicine*, 4(11), 2016.

[15] MD Devika, Cª Sunitha, and Amal Ganesh. Sentiment analysis: a comparative study on different approaches. *Procedia Computer Science*, 87:44–49, 2016.

[16] Piyush Kumar, Rishi Chauhan, Thompson Stephan, Achyut Shankar, and Sanjeev Thakur. A machine learning implementation for mental health care. application: Smart watch for depression detection. In *2021 11th International*

Conference on Cloud Computing, Data Science & Engineering (Confluence), pages 568–574. IEEE, 2021.

[17] Md Sabab Zulfiker, Nasrin Kabir, Al Amin Biswas, Tahmina Nazneen, and Mohammad Shorif Uddin. An in-depth analysis of machine learning approaches to predict depression. *Current research in behavioral sciences*, 2:100044, 2021.

[18] Suyash Dabhane and Pramila M Chawan. Depression detection on social media using machine learning techniques: A survey. *International Research Journal Of Engineering And Technology*, 2020.

[19] David William and Derwin Suhartono. Text-based depression detection on social media posts: A systematic literature review. *Procedia Computer Science*, 179: 582–589, 2021.

[20] Faisal Muhammad Shah, Farzad Ahmed, Sajib Kumar Saha Joy, Sifat Ahmed, Samir Sadek, Rimon Shil, and Md Hasanul Kabir. Early depression detection from social network using deep learning techniques. In *2020 IEEE Region 10 Symposium (TENSYMP)*, pages 823–826. IEEE, 2020.

[21] Tushtee Varshney, Sonam Gupta, and Charu Agarwal. Depression detection from social site using machine learning and deep learning. In *Mobile Computing and Sustainable Informatics*, pages 599–611. Springer, 2022.

[22] Salma Almouzini, Asem Alageel, et al. Detecting arabic depressed users from twitter data. *Procedia Computer Science*, 163:257–265, 2019.

[23] Keshu Malviya, Bholanath Roy, and SK Saritha. A transformers approach to detect depression in social media. In *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, pages 718–723. IEEE, 2021.

[24] Yunjing An, Shutao Sun, and Shujuan Wang. Naive bayes classifiers for music emotion classification based on lyrics. In *2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS)*, pages 635–638. IEEE, 2017.

[25] Jesia Quader Yuki, Md Mahfil Quader Sakib, Zaisha Zamal, Sabiha Haque Efel, and Mohammad Ashrafuzzaman Khan. Detecting depression from human conversations. In *Proceedings of the 8th International Conference on Computer and Communications Management*, pages 14–18, 2020.

[26] S Kayalvizhi and D Thenmozhi. Data set creation and empirical analysis for detecting signs of depression from social media postings. *arXiv preprint arXiv:2202.03047*, 2022.

[27] Joshua Y Kim, Greyson Y Kim, and Kalina Yacef. Detecting depression in dyadic conversations with multimodal narratives and visualizations. In *Australasian joint conference on artificial intelligence*, pages 303–314. Springer, 2019.

[28] Vishakha Arya and Amit Kumar Mishra. Machine learning approaches to mental stress detection: a review. *Annals of Optimization Theory and Practice*, 4 (2):55–67, 2021.

[29] SJ Pachouly, Gargee Raut, Kshama Bute, Rushikesh Tambe, and Shruti Bhavsar. Depression detection on social media network (twitter) using sentiment analysis. *Int. Res. J. Eng. Technol*, 8:1834–1839, 2021.

[30] Ravinder Ahuja and Alisha Banga. Mental stress detection in university students using machine learning algorithms. *Procedia Computer Science*, 152:349–353, 2019.

[31] Rutuja K Bhoge, Snehal A Nagare, Swapanali P Mahajan, and Prajakta S Kor. Depression detection by analyzing social media post of user. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, 2022.

[32] Sofia Arora, Arun Malik, Parul Khurana, and Isha Batra. Depression detection during the covid 19 pandemic by machine learning techniques. In *Advanced Informatics for Computing Research: 4th International Conference, ICAICR*

2020, Gurugram, India, December 26–27, 2020, Revised Selected Papers, Part I, pages 141–151. Springer, 2021.

[33] Bernice Yeow Ziwei and Hui Na Chua. An application for classifying depression in tweets. In *Proceedings of the 2nd International Conference on Computing and Big Data*, pages 37–41, 2019.

[34] Chiara Zucco, Barbara Calabrese, and Mario Cannataro. Sentiment analysis and affective computing for depression monitoring. In *2017 IEEE international conference on bioinformatics and biomedicine (BIBM)*, pages 1988–1995. IEEE, 2017.

[35] Felipe T Giuntini, Mirela T Cazzolato, Maria de Jesus Dutra dos Reis, Andrew T Campbell, Agma JM Traina, and Jo Ueyama. A review on recognizing depression in social networks: challenges and opportunities. *Journal of Ambient Intelligence and Humanized Computing*, 11(11):4713–4729, 2020.

[36] Hilman Wisnu, Muhammad Afif, and Yova Ruldevyani. Sentiment analysis on customer satisfaction of digital payment in indonesia: A comparative study using knn and naïve bayes. In *Journal of Physics: Conference Series*, volume 1444, page 012034. IOP Publishing, 2020.

[37] Usama Rehman, Mohammad G Shahnawaz, Neda H Khan, Korsi D Kharshiing, Masrat Khursheed, Kaveri Gupta, Drishti Kashyap, and Ritika Uniyal. Depression, anxiety and stress among indians in times of covid-19 lockdown. *Community mental health journal*, 57(1):42–48, 2021.

[38] Matthew W Gallagher, Michael J Zvolensky, Laura J Long, Andrew H Rogers, and Lorra Garey. The impact of covid-19 experiences and associated stress on anxiety, depression, and functional impairment in american adults. *Cognitive Therapy and Research*, 44(6):1043–1051, 2020.

[39] Dilaver Tengilimoğlu, Aysu Zekioğlu, Nurperihan Tosun, Oğuz Işık, and Onur Tengilimoğlu. Impacts of covid-19 pandemic period on depression, anxiety and

stress levels of the healthcare employees in turkey. *Legal Medicine*, 48:101811, 2021.

[40] Gonca Ustun. Determining depression and related factors in a society affected by covid-19 pandemic. *International Journal of Social Psychiatry*, 67(1):54–63, 2021.

[41] Nader Salari, Amin Hosseinian-Far, Rostam Jalali, Aliakbar Vaisi-Raygani, Shna Rasoulpoor, Masoud Mohammadi, Shabnam Rasoulpoor, and Behnam Khaledi-Paveh. Prevalence of stress, anxiety, depression among the general population during the covid-19 pandemic: a systematic review and meta-analysis. *Globalization and health*, 16(1):1–11, 2020.

[42] Edmond Pui Hang Choi, Bryant Pui Hung Hui, and Eric Yuk Fai Wan. Depression and anxiety in hong kong during covid-19. *International journal of environmental research and public health*, 17(10):3740, 2020.

[43] Petros Skapinakis, Stefanos Bellos, Achilleas Oikonomou, Georgios Dimitriadis, Paschalis Gkikas, Evridiki Perdikari, and Venetsanos Mavreas. Depression and its relationship with coping strategies and illness perceptions during the covid-19 lockdown in greece: a cross-sectional survey of the population. *Depression research and treatment*, 2020, 2020.

[44] Jianlong Zhou, Hamad Zogan, Shuiqiao Yang, Shoaib Jameel, Guandong Xu, and Fang Chen. Detecting community depression dynamics due to covid-19 pandemic in australia. *IEEE Transactions on Computational Social Systems*, 8 (4):982–991, 2021.

[45] Ochilbek Rakhmanov, Abdullah Demir, and Senol Dane. A brief communication: anxiety and depression levels in the staff of a nigerian private university during covid 19 pandemic outbreak. *J Res Med Dent Sci*, 8(3):118–122, 2020.

[46] Christoph Benke, Lara K Autenrieth, Eva Asselmann, and Christiane A Pané-Farré. Lockdown, quarantine measures, and social distancing: Associations

with depression, anxiety and distress at the beginning of the covid-19 pandemic among adults from germany. *Psychiatry research*, 293:113462, 2020.

[47] Zhijun Yin, Lina M Sulieman, and Bradley A Malin. A systematic literature review of machine learning in online personal health data. *Journal of the American Medical Informatics Association*, 26(6):561–576, 2019.

[48] Philipp Sterner, David Goretzko, and Florian Pargent. Everything has its price: Foundations of cost-sensitive learning and its application in psychology. *PsyArXiv*, 2021.

[49] Ammar Ismael Kadhim. Survey on supervised machine learning techniques for automatic text classification. *Artificial Intelligence Review*, 52(1):273–292, 2019.

[50] P Padhanarath, Y Aunhathaweesup, and S Kiattisin. Sentiment analysis and relationship between social media and stock market: pantip. com and set. In *IOP Conference Series: Materials Science and Engineering*, volume 620, page 012094. IOP Publishing, 2019.

[51] Mohammad Ehsan Basiri and Arman Kabiri. Homper: A new hybrid system for opinion mining in the persian language. *Journal of Information Science*, 46 (1):101–117, 2020.

[52] Andry Alamsyah and Earlyan Abdiel Bernatapi. Evolving customer experience management in internet service provider company using text analytics. In *2019 International Conference on ICT for Smart Society (ICISS)*, volume 7, pages 1–6. IEEE, 2019.

[53] Priyanka Arora and Parul Arora. Mining twitter data for depression detection. In *2019 International Conference on Signal Processing and Communication (ICSC)*, pages 186–189. IEEE, 2019.

[54] Mario Ezra Aragón, Adrián Pastor López Monroy, Luis Carlos González-Gurrola, and Manuel Montes. Detecting depression in social media using fine-grained emotions. In *Proceedings of the 2019 conference of the North American*

chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers), pages 1481–1486, 2019.

[55] Senthil Murugan Nagarajan and Usha Devi Gandhi. Classifying streaming of twitter data based on sentiment analysis using hybridization. *Neural Computing and Applications*, 31(5):1425–1433, 2019.

[56] Akkapon Wongkoblap, Miguel A Vadillo, Vasa Curcin, et al. Researching mental health disorders in the era of social media: systematic review. *Journal of medical Internet research*, 19(6):e7215, 2017.

[57] B Gnana Priya. Emoji based sentiment analysis using knn. *International Journal of Scientific Research and Review*, 7(4):859–865, 2019.

[58] Lifang Wu, Mingchao Qi, Meng Jian, and Heng Zhang. Visual sentiment analysis by combining global and local information. *Neural Processing Letters*, 51(3): 2063–2075, 2020.

[59] Shailja Gupta, Sachin Lakra, and Manpreet Kaur. Sentiment analysis using partial textual entailment. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, pages 51–55. IEEE, 2019.

[60] Cynthia Van Hee, Gilles Jacobs, Chris Emmery, Bart Desmet, Els Lefever, Ben Verhoeven, Guy De Pauw, Walter Daelemans, and Véronique Hoste. Automatic detection of cyberbullying in social media text. *PloS one*, 13(10):e0203794, 2018.

[61] Monica Malik, Sameena Naaz, and Iffat Rehman Ansari. Sentiment analysis of twitter data using big data tools and hadoop ecosystem. In *International conference on ISMAC in computational vision and bio-engineering*, pages 857–863. Springer, 2018.

[62] Aven Samareh, Yan Jin, Zhangyang Wang, Xiangyu Chang, and Shuai Huang. Detect depression from communication: how computer vision, signal processing,

and sentiment analysis join forces. *IISE Transactions on Healthcare Systems Engineering*, 8(3):196–208, 2018.

[63] Anneketh Vij and Jyotika Pruthi. An automated psychometric analyzer based on sentiment analysis and emotion recognition for healthcare. *Procedia computer science*, 132:1184–1191, 2018.

[64] Wenping Zhang, Mengna Xu, and Qiqi Jiang. Opinion mining and sentiment analysis in social media: Challenges and applications. In *International Conference on HCI in Business, Government, and Organizations*, pages 536–548. Springer, 2018.

[65] Abhilash Biradar and Shashikumar G Totad. Detecting depression in social media posts using machine learning. In *International Conference on Recent Trends in Image Processing and Pattern Recognition*, pages 716–725. Springer, 2018.

[66] Iram Fatima, Hamid Mukhtar, Hafiz Farooq Ahmad, and Kashif Rajpoot. Analysis of user-generated content from online social communities to characterise and predict depression degree. *Journal of Information Science*, 44(5):683–695, 2018.

[67] Mandar Deshpande and Vignesh Rao. Depression detection using emotion artificial intelligence. In *2017 international conference on intelligent sustainable systems (iciss)*, pages 858–862. IEEE, 2017.

[68] Maryam Mohammed Aldarwish and Hafiz Farooq Ahmad. Predicting depression levels using social media posts. In *2017 IEEE 13th international Symposium on Autonomous decentralized system (ISADS)*, pages 277–280. IEEE, 2017.

[69] Anees Ul Hassan, Jamil Hussain, Musarrat Hussain, Muhammad Sadiq, and Sungyoung Lee. Sentiment analysis of social networking sites (sns) data using machine learning approach for the measurement of depression. In *2017 international conference on information and communication technology convergence (ICTC)*, pages 138–140. IEEE, 2017.

[70] Sharath Chandra Guntuku, David B Yaden, Margaret L Kern, Lyle H Ungar, and Johannes C Eichstaedt. Detecting depression and mental illness on social media: an integrative review. *Current Opinion in Behavioral Sciences*, 18:43–49, 2017.

[71] Jaspreet Singh, Gurvinder Singh, and Rajinder Singh. Optimization of sentiment analysis using machine learning classifiers. *Human-centric Computing and information Sciences*, 7(1):1–12, 2017.

[72] Xiaohui Tao, Xujuan Zhou, Ji Zhang, and Jianming Yong. Sentiment analysis for depression detection on social networks. In *International Conference on Advanced Data Mining and Applications*, pages 807–810. Springer, 2016.

[73] D Alessia, Fernando Ferri, Patrizia Grifoni, and Tiziana Guzzo. Approaches, tools and applications for sentiment analysis implementation. *International Journal of Computer Applications*, 125(3), 2015.

[74] Abhishek Kaushik and Sudhanshu Naithani. A study on sentiment analysis: methods and tools. *Int. J. Sci. Res.(IJSR)*, 4(12):2319–7064, 2015.

[75] Shambhavi Dinakar, Pankaj Andhale, and Manjeet Rege. Sentiment analysis of social network content. In *2015 IEEE International Conference on Information Reuse and Integration*, pages 189–192. IEEE, 2015.

[76] Ekta Gupta, Geetanjali Rathee, Pardeep Kumar, Durg Singh Chauhan, et al. Mood swing analyser: a dynamic sentiment detection approach. *Proceedings of the National Academy of Sciences, India Section A: Physical Sciences*, 85(1): 149–157, 2015.

[77] Wei Yang and Lan Mu. Gis analysis of depression among twitter users. *Applied Geography*, 60:217–223, 2015.

[78] Giorgio Maria Di Nunzio. A new decision to take for cost-sensitive naïve bayes classifiers. *Information Processing & Management*, 50(5):653–674, 2014.

[79] Xinyu Wang, Chunhong Zhang, Yang Ji, Li Sun, Leijia Wu, and Zhana Bao. A depression detection model based on sentiment analysis in micro-blog social network. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 201–213. Springer, 2013.

[80] Chung-Chian Hsu, Yan-Ping Huang, and Keng-Wei Chang. Extended naive bayes classifier for mixed data. *Expert Systems with Applications*, 35(3):1080–1083, 2008.

[81] Cuiyan Wang, Riyu Pan, Xiaoyang Wan, Yilin Tan, Linkang Xu, Roger S McIntyre, Faith N Choo, Bach Tran, Roger Ho, Vijay K Sharma, et al. A longitudinal study on the mental health of general population during the covid-19 epidemic in china. *Brain, behavior, and immunity*, 87:40–48, 2020.

[82] Rümeysa Yeni Elbay, Ayşe Kurtulmuş, Selim Arpacıoğlu, and Emrah Karadere. Depression, anxiety, stress levels of physicians and associated factors in covid-19 pandemics. *Psychiatry research*, 290:113130, 2020.

[83] Cindy H Liu, Emily Zhang, Ga Tin Fifi Wong, Sunah Hyun, et al. Factors associated with depression, anxiety, and ptsd symptomatology during the covid-19 pandemic: Clinical implications for us young adult mental health. *Psychiatry research*, 290:113172, 2020.

[84] Chiara Pomare, Janet C Long, Kate Churruca, Louise A Ellis, and Jeffrey Braithwaite. Social network research in health care settings: design and data collection. *Social networks*, 2019.

[85] Daniel Schneider and Kristen Harknett. What's to like? facebook as a tool for survey data collection. *Sociological Methods & Research*, 51(1):108–140, 2022.

[86] Mandy M Archibald, Rachel C Ambagtsheer, Mavourneen G Casey, and Michael Lawless. Using zoom videoconferencing for qualitative data collection: perceptions and experiences of researchers and participants. *International journal of qualitative methods*, 18:1609406919874596, 2019.

[87] NE Morrell-Scott. Using diaries to collect data in phenomenological research. *Nurse researcher*, 25(4):26–29, 2018.

[88] Owen Doody and Maria Noonan. Preparing and conducting interviews to collect data. *Nurse researcher*, 20(5), 2013.

[89] Elizabeth May Carr, Gary Dezhi Zhang, Jane (Hung) Yeong Ming, and Zarrin Seema Siddiqui. Qualitative research: An overview of emerging approaches for data collection. *Australasian Psychiatry*, 27(3):307–309, 2019.

[90] Yuji Roh, Geon Heo, and Steven Euijong Whang. A survey on data collection for machine learning: a big data-ai integration perspective. *IEEE Transactions on Knowledge and Data Engineering*, 33(4):1328–1347, 2019.

[91] Apoorv Agarwal, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca J Passonneau. Sentiment analysis of twitter data. In *Proceedings of the workshop on language in social media (LSM 2011)*, pages 30–38, 2011.

[92] Dean E Wendt and Richard M Starr. Collaborative research: an effective way to collect data for stock assessments and evaluate marine protected areas in california. *Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science*, 1(1):315–324, 2009.

[93] Danxia Liu, Xing Lin Feng, Farooq Ahmed, Muhammad Shahid, Jing Guo, et al. Detecting and measuring depression on social media using a machine learning approach: systematic review. *JMIR Mental Health*, 9(3):e27244, 2022.

[94] Kuhaneswaran AL Govindasamy and Naveen Palanichamy. Depression detection using machine learning techniques on twitter data. In *2021 5th international conference on intelligent computing and control systems (ICICCS)*, pages 960–966. IEEE, 2021.

[95] Taiwo Oladipupo Ayodele. Types of machine learning algorithms. *New advances in machine learning*, 3:19–48, 2010.

[96] S Smys and Jennifer S Raj. Analysis of deep learning techniques for early detection of depression on social media network-a comparative study. *Journal of trends in Computer Science and Smart technology (TCSST)*, 3(01):24–39, 2021.

[97] Anu Priya, Shruti Garg, and Neha Prerna Tigga. Predicting anxiety, depression and stress in modern life using machine learning algorithms. *Procedia Computer Science*, 167:1258–1267, 2020.

[98] Kaj Sparle Christensen and Minna Sparle-Christensen. Comparing the construct validity of the patient health questionnaire (phq-9) and the major depression inventory (mdi) using rasch analysis. *Journal of Affective Disorders*, 333:44–50, 2023.

[99] Swati Jain, Suraj Prakash Narayan, Rupesh Kumar Dewang, Utkarsh Bhartiya, Nalini Meena, and Varun Kumar. A machine learning based depression analysis and suicidal ideation detection system using questionnaires and twitter. In *2019 IEEE Students Conference on Engineering and Systems (SCES)*, pages 1–6. IEEE, 2019.

[100] Nikhil Marriwala, Deepti Chaudhary, et al. A hybrid model for depression detection using deep learning. *Measurement: Sensors*, 25:100587, 2023.

[101] Pratyaksh Jain, Karthik Ram Srinivas, and Abhishek Vichare. Depression and suicide analysis using machine learning and nlp. In *Journal of Physics: Conference Series*, volume 2161, page 012034. IOP Publishing, 2022.

[102] Hritik Nandanwar and Sahiti Nallamolu. Depression prediction on twitter using machine learning algorithms. In *2021 2nd Global Conference for Advancement in Technology (GCAT)*, pages 1–7. IEEE, 2021.

[103] Md Rafiqul Islam, Abu Raihan M Kamal, Naznin Sultana, Robiul Islam, Mohammad Ali Moni, et al. Detecting depression using k-nearest neighbors (knn)

classification technique. In *2018 International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, pages 1–4. IEEE, 2018.

[104] Habibollah Ghassemzadeh, Ramin Mojtabai, Narges Karamghadiri, and Narges Ebrahimkhani. Psychometric properties of a persian-language version of the beck depression inventory-second edition: Bdi-ii-persian. *Depression and anxiety*, 21(4):185–192, 2005.

[105] Nancy Devlin, David Parkin, Bas Janssen, Nancy Devlin, David Parkin, and Bas Janssen. An introduction to eq-5d instruments and their applications. *Methods for analysing and reporting EQ-5D data*, pages 1–22, 2020.

[106] Paramdeep Singh, Jawahar Singh, Sameer Peer, Manav Jindal, Sunil Khokhar, Abhilash Ludhiadch, and Anjana Munshi. Assessment of resting-state functional magnetic resonance imaging connectivity among patients with major depressive disorder: A comparative study. *Annals of Neurosciences*, page 09727531231191889, 2023.

[107] Danilo Carrozzino, Chiara Patierno, Giovanni A Fava, and Jenny Guidi. The hamilton rating scales for depression: a critical review of clinimetric properties of different versions. *Psychotherapy and psychosomatics*, 89(3):133–150, 2020.

[108] Magnus Vestin, Marie Åsberg, Marie Wiberg, Eva Henje, and Inga Dennhag. Psychometric validity of the montgomery and åsberg depression rating scale for youths (madrs-y). *Nordic Journal of Psychiatry*, 77(5):421–431, 2023.

[109] Per Bech. Rating scales in depression: limitations and pitfalls. *Dialogues in clinical neuroscience*, 2022.

[110] Allison Lino, Timothy A Erickson, Melissa S Nolan, Kristy O Murray, and Shannon E Ronca. A preliminary study of proinflammatory cytokines and depression following west nile virus infection. *Pathogens*, 11(6):650, 2022.

[111] Rachel L Goldin, Johnny L Matson, Matthew J Konst, and Hilary L Adams. A comparison of children and adolescents with asd, atypical development, and typical development on the behavioral assessment system for children, (basc-2). *Research in Autism Spectrum Disorders*, 8(8):951–957, 2014.

[112] Symon M Kariuki, Charles RJC Newton, Amina Abubakar, Mary A Bitta, Rachael Odhiambo, and Jacqueline Phillips Owen. Evaluation of psychometric properties and factorial structure of adhd module of k-sads-pl in children from rural kenya. *Journal of attention disorders*, 24(14):2064–2071, 2020.

[113] German Eduardo Rueda-Jaimes, Vanessa Alexandra Castro-Rueda, Andrés Mauricio Rangel-Martínez-Villalba, Catalina Moreno-Quijano, Gustavo Adolfo Martinez-Salazar, and Paul Anthony Camacho. Validation of the beck hopelessness scale in patients with suicide risk. *Revista de Psiquiatría y Salud Mental (English Edition)*, 11(2):86–93, 2018.

[114] E Sherwood Brown, Michelle Murray, Thomas J Carmody, Beth D Kennard, Carroll W Hughes, David A Khan, and A John Rush. The quick inventory of depressive symptomatology-self-report: a psychometric evaluation in patients with asthma and major depressive disorder. *Annals of Allergy, Asthma & Immunology*, 100(5):433–438, 2008.

[115] Nelson B Rodrigues, Roger S McIntyre, Orly Lipsitz, Danielle S Cha, Yena Lee, Hartej Gill, Amna Majeed, Lee Phan, Flora Nasri, Roger Ho, et al. Changes in symptoms of anhedonia in adults with major depressive or bipolar disorder receiving iv ketamine: results from the canadian rapid treatment center of excellence. *Journal of Affective Disorders*, 276:570–575, 2020.

[116] Joseph Ford, Felicity Thomas, Richard Byng, and Rose McCabe. Use of the patient health questionnaire (phq-9) in practice: Interactions between patients and physicians. *Qualitative Health Research*, 30(13):2146–2159, 2020.

[117] Abdallah Abu Khait, Louise Reagan, and Juliette Shellman. Uses of reminiscence intervention to address the behavioral and psychosocial problems associated with dementia: An integrative review. *Geriatric Nursing*, 42(3):756–766, 2021.

[118] Ali Montazeri, Azita Goshtasebi, Mariam Vahdaninia, and Barbara Gandek. The short form health survey (sf-36): translation and validation study of the iranian version. *Quality of life research*, 14:875–882, 2005.

[119] Marc J Gameroff, Priya Wickramaratne, and Myrna M Weissman. Testing the short and screener versions of the social adjustment scale–self-report (sas-sr). *International journal of methods in psychiatric research*, 21(1):52–65, 2012.

[120] Femke Verduin, Willem F Scholte, Theoneste Rutayisire, Wim B Busschers, and Karien Stronks. The validation of a social functioning questionnaire in an african postconflict context. *Transcultural Psychiatry*, 51(2):228–246, 2014.

[121] Perla Massai, Francesca Colalelli, Julita Sansoni, Donatella Valente, Marco Tofani, Giovanni Fabbrini, Andrea Fabbrini, Michela Scuccimarri, and Giovanni Galeoto. Reliability and validity of the geriatric depression scale in italian subjects with parkinson's disease. *Parkinson's Disease*, 2018, 2018.

[122] Jorge Guardiola and Andrés J Picazo-Tadeo. Building weighted-domain composite indices of life satisfaction with data envelopment analysis. *Social Indicators Research*, 117:257–274, 2014.

[123] Dongmei Wu, Taolin Chen, Hao Yang, Qiyong Gong, and Xiuying Hu. Verbal responses, depressive symptoms, reminiscence functions and cognitive emotion regulation in older women receiving individual reminiscence therapy. *Journal of clinical nursing*, 27(13-14):2609–2619, 2018.

[124] Uma Yadav, Ashish K Sharma, and Dipti Patil. Review of automated depression detection: Social posts, audio and video, open challenges and future direction. *Concurrency and Computation: Practice and Experience*, 35(1):e7407, 2023.

[125] Payam Kaywan, Khandakar Ahmed, Ayman Ibaida, Yuan Miao, and Bruce Gu. Early detection of depression using a conversational ai bot: A non-clinical trial. *Plos one*, 18(2):e0279743, 2023.

[126] Sofia Arora, Arun Malik, Mohammad Shabaz, and Evans Asenso. Machine learning based model for detecting depression during covid-19 crisis. *Scientific African*, page e01716, 2023.

Publications

Published/Accepted articles

[1] Sofia Arora, Arun Malik, Parul Khurana, and Isha Batra. ”Depression Detection During the Covid 19 Pandemic by Machine Learning Techniques.” In Advanced Informatics for Computing Research: 4th International Conference, ICAICR 2020, Gurugram, India, December 26–27, 2020, Revised Selected Papers, Part I, pp. 141-151. Singapore: Springer Singapore, 2021. (Published, Scopus indexed)

[2] Sofia Arora, and Arun Malik. ”A Systematic Review on Sentiment Analysis for The Depression Detection During Covid-19 Pandemic.” In 2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), pp. 1-6. IEEE, 2022. (Published, Scopus indexed)

[3] Sofia Arora, Arun Malik, Mohammad Shabaz, and Evans Asenso. ”Machine Learning based Model for Detecting Depression During Covid-19 Crisis.” Scientific African (2023): e01716. (Published, Scopus indexed)