AN APPROACH FOR REDUCING GAPS IN EVALUATION MECHANISM FOR BETTER LEARNING OUTCOMES USING MACHINE LEARNING

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Transforming Education Transforming India

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DEDICATION

This Thesis is a tribute to my parents, especially my mother," **Mrs. Sandhya Devi**," and my husband "**Mr. Naresh Kumar**", for encouraging me to pursue this study. They always motivated me to overcome all difficulties and remain positive & finding solutions. They always kept calm, and positive & supported me unconditionally in all possible manners. I couldn't have made it through without my husband's support. His support and help in all aspects gave me the courage to face difficult times. Further, I would like to thank my sweet son, "**Namish Rana**" for understanding the value of my time, co-operating and still making me feel happy with his sweet & lovely talks.

DECLARATION

I, hereby declare that the presented work in the thesis entitled "An approach for reducing gaps in evaluation mechanism for better learning outcomes using machine learning" in fulfillment degree of **Doctor of Philosophy (Ph. D.)** is an outcome of research work carried out by me under the supervision Prof.(Dr.) Lovi Raj Gupta, working as Pro Vice-Chancellor and Prof.(Dr.) Mithilesh Kumar Dubey, working as a Professor, in the School of Computer Applications of Lovely Professional University, Punjab, India. In accordance with conventional scientific reporting procedure, proper recognition has been provided wherever work discussed here is based on the results of other investigators. This work had not been submitted in whole or in part to any other University or Institute for the award of a degree.

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CERTIFICATE

This is to confirm that the student's declaration statement is accurate to the best of our knowledge and belief. Under our direction and supervision, she has completed her Ph.D. thesis "An approach for reducing gaps in evaluation mechanism for better learning outcomes using machine learning". The present work is the result of her original investigation, effort, and study. No other university has ever used any of the work for another degree. Accordingly, the doctoral thesis is suitable for the submission and fulfillment of the requirements of the Lovely Professional University Phagwara, a Ph.D. degree in Computer Applications.

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ABSTRACT

Education is an important part of our lives. It carries different meanings to different people. Education prepares us to lead our social life smoothly. A person's education is a most important asset. Education provides lots of benefits to all, which can be at a personal level, social level or monitory level. Education is a tool that provides individuals with expertise, technique, and facts, allowing them to comprehend their family, community, and Nation's rights and obligations. Education is the process of giving or gaining knowledge as well as improving thinking and judgment skills. Education contributes to the progress of a country. As a result, the importance of education in life and society cannot be overstated. Learning outcomes of the students play a crucial role in the students learning. Learning, outcomes, assessment, and course learning outcomes are the fundamental terms used in the education system. Learning acquiring new knowledge, behavior, skill, value and understanding and outcomes takes place when learners are clear about what they should be able to do. Assessment is the measure of how much attainment of the outcome is being done and course Learning Outcomes (LO) is a well-described point-wise knowledge, skills, and aptitudes that a particular course is designed to imbibe in the learner. There is a need for Assessing LO to assess how much the student is grasping and is aligned with the designed LO of the course. There are two aspects of assessing the translation of knowledge during the teaching-learning process. One is a direct measure wherein the learners are assessed based on scores they gauge in the tests, midterm, and end-term examinations, etc. and the second is how much students are engaged and emerge while sitting in the class. In the recent years, the system of student learning and emotions related to academia has been treated seriously to reengineer the process of teaching and learning at all levels of education. In the current scenario, it is a big challenge to cover both aspects of students' learning outcomes i.e. academic emotions and their overall attainment. These aspects of learning are equally important. In the existing situation, quantitative and qualitative learning outcome assessments are used independently with no associativity, which has been identified as a

significant limitation in the current study. Test scores, mid-term examination scores, end-of-term examination scores, and so on are referred to as quantitative measurements. Whereas storing academic emotions i.e. how much students are engaged & emerged during the class and the same are referred to as qualitative measures. Feedback is a key to gauging the association and participation of an individual with a process, product, and service being rendered. Feedback become more prominent and important in teaching-learning practices as the feedback reveals the performance and the happening inside the class/teaching-learning session. The feedback can be quantitative or qualitative. The quantitative feedback of the education is through assessment done for particular courses and there is a dearth of qualitative feedback for every lecture being conducted. Real-time Academic emotions of the students represent the quality of various aspects of the content i.e. qualitative data. Changing pedagogy or assessment criteria is a traditional technique to enhance learning results, but here a fresh notion is offered in which academic emotions might serve as an additional metric to correlate learning outcomes. The objective of the proposed study is to collate qualitative and quantitative measures of student learning to retrieve the true learning outcomes of the students. A new framework has been developed to capture the Academic emotions of the students in real-time about lectures. This framework i.e. Teaching Effectiveness Rating Engine (TERE) stores students' emotions on five parameters such as quality of content, Examples/ Application, Doubt clearing & Interaction, Quality of Delivery, and Value addition on five Lickert scales from unhappy to happy. A unique concept is proposed in which academic emotions are combined with quantitative assessment to explain the causes of underperformance. The proposed technique uses machine learning to relate both quantitative and qualitative measures of students' learning and creates the reason why knowledge translation is not occurring at the micro-level for each course's learning goals. Course attainment which is a quantitative measure of learning in a particular course is generally calculated at the end of the semester but the proposed study highlighted that course attainment can be measured after assignments,

midterm, and end-term, and questions are mapped to the course outcomes (COs) mentioned in a particular course either theory or practical. The increasing role of Artificial Intelligence (AI) and Machine Learning has changed its shape and scope in different branches of the education sector. AI is going to add new features instead of changing the whole traditional system in education. The growing prominence of Machine Learning (ML) has altered the opportunity and paradigm of education across its many fields. Proper application of machine learning techniques in the education industry enables pupils to accomplish their tasks more effectively. Based on students' quantitative performance and real-time feedback, an intelligent model is created. Machine learning approaches use a learning process that trains the machine to do the task automatically. Machine learning algorithms are used to assess, predict, and curate judgments using mathematical models. In the proposed study an intelligent model has been prepared to consider both qualitative and quantitative measures of students' learning outcomes. K-means cluster is used to find the threshold and prediction of the student learning outcomes respectively. The processing of the aggregation model is performed to get real-time results for each semester of a particular course. The accomplishment analysis of the prediction model is compared concerning to score and mean square error. Results of k-means clustering and the proposed intelligent algorithm with stacking give preferable prediction outcomes compared to other existing methods like linear regression, decision tree regressor, gradient boosting regressor, and random forest. The score for the proposed intelligent model was 0.66 for validation. The proposed model will help in improving student learning outcomes and identify the reasons why overall attainment is not achieved. The proposed model is capable of diving deep into the micro-level of each class's learning outcome and enjoins the qualitative review given by the student for that class to curate the reasons for the expected translation of knowledge not happening. The model is unique and would pave new dimensions of unraveling truthful reasons for underperformance lecture-wise so that dynamic updations in the teaching-learning process can be done. The present study presents that quantitative

measures can be gauged at any time during the semester whereas conventionally, it is calculated after the completion of the semester. Student learning outcomes can be improved without changing existing pedagogy or assessment criteria. Machine learning is used to present a novel idea wherein academic emotion measures supplement the quantitative measure of learning at the micro-level, i.e. lecture-wise.

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First, I would like to thank God for making things possible, always keeping hope alive, and putting me under the supervision of such an inspirational personality. Further, I would like to express my sincere gratitude to my Supervisor Dr. Lovi Raj Gupta for guiding/helping/motivating me and for everything he did on each & every step during the research. It is really rare to find a person of such great caliber, but still so punctual, hardworking, kind, humble, approachable, and many more. He is someone whose life is a role model for me & many others and his knowledge, vision & kindness inspired me to overcome all the difficulties. Pursuing a Ph.D. under his Guidance was a wonderful experience which I will, definitely cherish throughout my career and life.

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LIST OF ABBREVIATIONS

Abbreviation	Description
EDM	Educational Data Mining
CET	Continuing education & training
AI	Artificial Intelligence
NBA	National board of accreditation
CO	Course Outcomes
PO	Program Outcomes
LO	Learning Outcomes
MOOCs	Massive open online course
EDT	Educational development target
CHEA	Council for Higher Education Accreditations
CIQG	International Quality Group
SLE	Student learning experience
IoT	Internet of things
DSLO	Deaf Students Learning Outcomes
MSA	Multisource assessment
ITS	Intelligent Tutorial Systems
NHL	National hockey league
ANN	Artificial neural networks
XG BOOST	Extreme Gradient Boosting
SVM	Support Vector Machine
CNN	Convolutional neural networks
LR	Linear regression
GBDT	Gradient boosting decision tree
ANN	Artificial Neural Network
MST	Mid-semester test
EST	End semester test
MCQ	Multiple choice question
CGPA	Cumulative Grade Point Average

SGPA	Semester Grade Point Average
MTT	Mid Term Test
ETT	End term test
MIN	Minimum rating
MAX	Maximum rating
AVG	Student's average rating
IP	Instruction plan
COs	Course outcomes
TERE	Teaching effectiveness rating engine
DT	Decision Tree
CART	Classification and Regression Tree
RegistrationNo	Student registration number
LectureN	Lecture number
TeacherID	Teacher identity
BOS	Board of Studies

CHAPTER 1

INTRODUCTION

1.1 Introduction

Education is a lifelong process leading to learning and realizing aspirations. Knowledge can be gained from parents, teachers, friends, neighbors, and experiences as well. All forms of learning that benefit mankind and nature are encompassed under education. To expand the excellence of the present education system emotional intelligence needs to be implemented. Emotional intelligence can help in improving education and students [1]. When it comes to tackling a variety of issues to prevent actions connected to mental health, emotional intelligence is crucial. If student emotions are recorded, it will benefit academic performance [2] [3]. Emotions play a pivotal role in academic contexts, particularly in how emotions signify student engagement and learning. Why do students feel emotions? How do emotions impact learning engagement and achievement? How can institutions employ emotional resources to engage and achieve learning outcomes?

However, to understand the ingrained knowledge of students learning, students' academic emotions need to be measured. The easiest way to evaluate and support students' learning is to capture feedback on learning outcomes. The role of cognitive and motivational parameters is better understood than emotional assessment. But academic emotions along with their feedback play an important role in students' learning [4]. Emotions are very important in capturing feedback as other parameters like motivation, social factors, cognitive skills, etc. but their role is recently been recognized. Therefore it is crucial to consider both sides of education. Following an extensive examination of the literature, it is discovered that most research only takes into account either qualitative or quantitative measures [5].

Education can help in social, personal, and economic upheave of life. To live a smooth social life education can benefit every step of life. Understanding of rights and responsibilities towards family, society, and Nation increases with knowledge gained through education. It broadens one's view and outlook on the world. It adds value to your societal presence and it helps in building morals, ethics, and values. Learning is the major factor that is related to education. Education is a process of imparting or obtaining knowledge. Knowledge can enhance and supplement capabilities of reasoning and judgment. Understanding things becomes better with knowledge. It is one of the most important aspects of an individual's success. Education is instrumental in overcoming all worldly problems. A country’s growth is associated with the growth of education in that Nation. Thus, the role of education is deep-rooted in our life and society. People may learn skills, techniques, and information through education, which enables them to understand their duties towards their relations, society, and Nation.

Education is an important part of our lives. It carries different meanings for different people. For a student, education may be a degree, at the same time, for a teacher, it may be an opportunity to build good human beings who can help society by spreading knowledge. For an entrepreneur, education may be a source of growing business [6]. Elucidation is a major factor related to education. Understanding things becomes better with knowledge. It is one of the most important aspects of an individual's success. Education is viewed as the key to a better life. A nation develops as its level of education rises. Within the study area, significant approaches such as data mining, machine learning, and statistical techniques in educational data mining (EDM) are applied in schools and academic institutions. Various methods and algorithms are used in educational data to design a better mechanism to get better overall performance. Specialization courses are created to improve technical education after secondary education. Improvement in student performance is the top priority of higher educational institutions. Mapping students’ present situations is required before designing the program. The use of machine learning is also incorporated into the education sector [7] [8] [9].

Education is playing an important role in our lives. Environmental sustainability is affected by technology and education. Education and

Information Technology help in endorsing it [10]. The educational system is significantly impacted by technology. The recent COVID-19 Pandemic has enhanced the authority of adopting digital technologies in education. The entire teaching and learning environment has experienced a paradigm shift as a result of these digital tools. It functions as a guide, a reviewer, and a co-creator of material in addition to sharing knowledge. Students' lives have been simpler as a result of educational technology advancements. Nowadays, students prepare presentations and projects utilizing a variety of software and tools rather than writing on paper. A tablet is quite lightweight when compared to a stack of laptops. The navigation of an E-book is simpler than that of a large book. These methods and means contribute to raising research interest too. Major uses and difficulties in education are discussed in the need for digital technology in education. It is also important for the welfare and security of the human being [11] [12]. Civilization is currently undergoing a sea change. The need of the hour is highly qualified technical and managerial people who can re-imagine the effective, efficient, and sustained ecosystem that can rapidly and effectively close the gaps. A strong focus on Continuing Education & Training (CET) programs at all levels must be implemented to achieve this crucial aim [13]. Nowadays proactive or active actions are required to identify students with slow and fast pace of learning [14].

In daily life appearance of Artificial Intelligence (AI) in the form of machine learning is very common and revolutionized the education system as well [15]. Artificial intelligence-driven technologies in education are becoming more and more common these days. Integrated artificial intelligence has several advantages in the field of education. It can be widely applied in areas like learning, adaptive assistance, global classroom opportunities, student grading, intelligent tutoring systems, adaptive courseware, and administrative tools [16] [17]. Artificial intelligence methods, such as deep learning, machine learning, artificial neural networks, natural language processing, and genetic algorithms have made it possible to create intelligent environments that facilitate behavior identification, model building, and personalized recommendations for educational resources. AI and ML will have an increasingly important role in higher education as it allows students to have a personalized approach to learning issues based on their unique experiences and preferences [18] [19]. Machine learning, a branch of AI has gained popularity in areas like test score prediction, early failure detection, and risk assessment of students [20]. With the help of algorithms, teachers can customize learning for each student by analyzing data, seeing trends, and making predictions. The efficiency and productivity of learning systems can be increased as per the necessity of students with the use of machine learning [21] [22] [23] [24].

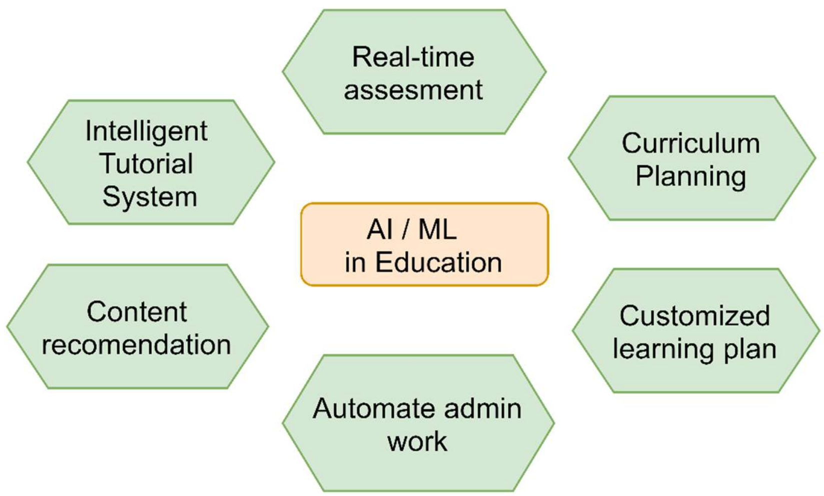

Figure 1. 1 Significance of AI and ML in education

Figure 1. 1 elaborates on the significance of AI and ML in education. AI and ML algorithms can be used for intelligent tutors, dropout predictions, performance predictions, adaptive and predictive learning and learning styles, analytics and group-based learning, and automation. Machine learning is a science that trains computer systems to think and behave like humans autonomously. Here, the machine learns from the previous experiences. Machine learning is popular in various fields like education, healthcare, food, transportation, etc. Using machine learning computer systems collect data, understand it, and transmit the decision based on the current and previous results. Three basic categories of machine learning are Supervised,

Unsupervised, and Reinforcement Learning. Supervised, Unsupervised, and Reinforcement Learning are the three fundamental categories of machine learning techniques [25].

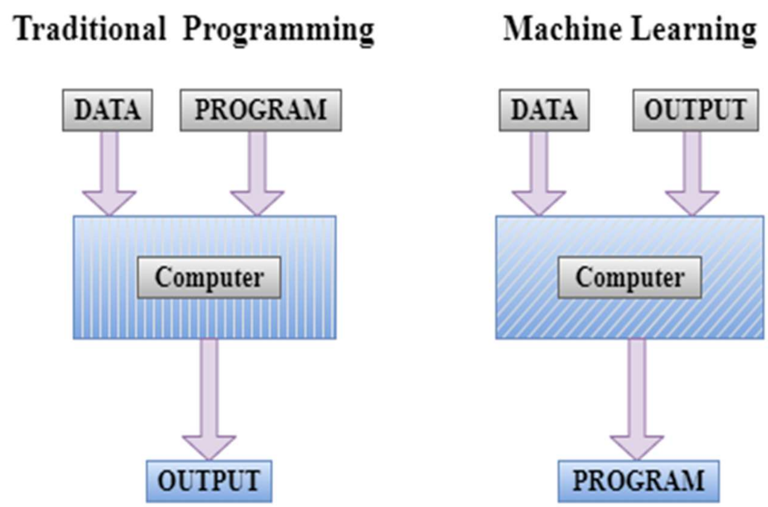

Figure 1. 2 Traditional Programming versus Machine Learning

Figure 1. 2 depicts the process of traditional programming versus Machine Learning. The working of both is different as shown in Figure 1-2. Supervised learning: Supervised learning, in the context of artificial intelligence and machine learning, is a type of system in which both input and desired output data are provided. Input and output data are labeled for classification to provide a learning basis for future data processing. Classification is used when we want to map input to output labels (using discrete values), and regression when we want to map input to a continuous output. Supervised learning problems can be further grouped into

- Regression Algorithm.
- Classification.

Decision tree, Naïve Bayes, linear regression, and random forest for both classification and regression problems are some popular examples of supervised machine learning algorithms [26].

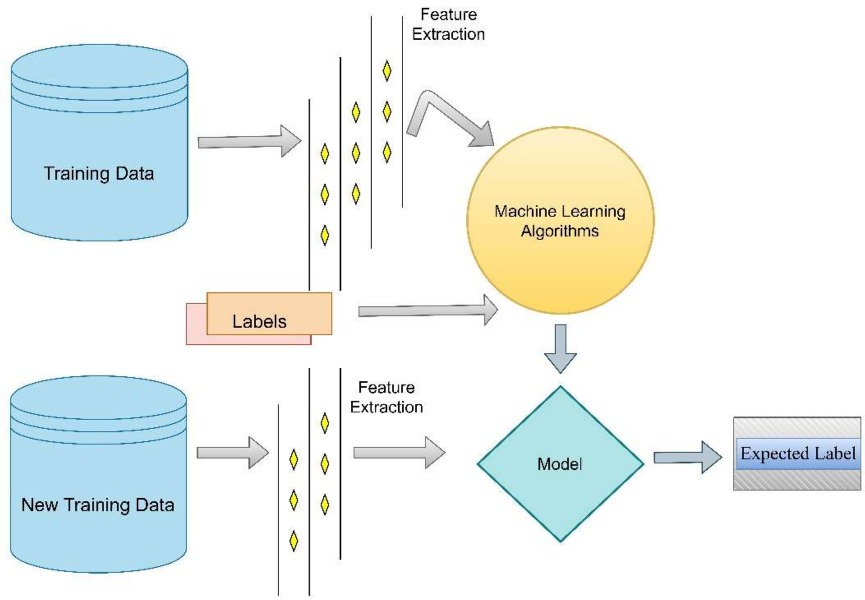

Figure 1. 3 Supervised machine learning process

Figure 1. 3 depicts the working of supervised learning in machine learning. In the case of supervised learning labels are given whereas in the case of unsupervised learning, labels are not given.

Unsupervised learning: In a given dataset with information that is neither labeled nor classified trained using unsupervised learning. Similarities and patterns in the given dataset have been used to group unsorted information. Therefore, unsupervised learning works on the information without guidance. Unsupervised learning problems can be further grouped into

- Clustering
- Association

k-means for clustering, Hierarchical clustering, Apriori algorithm for association rule learning problems are some popular examples of unsupervised learning algorithms [27].

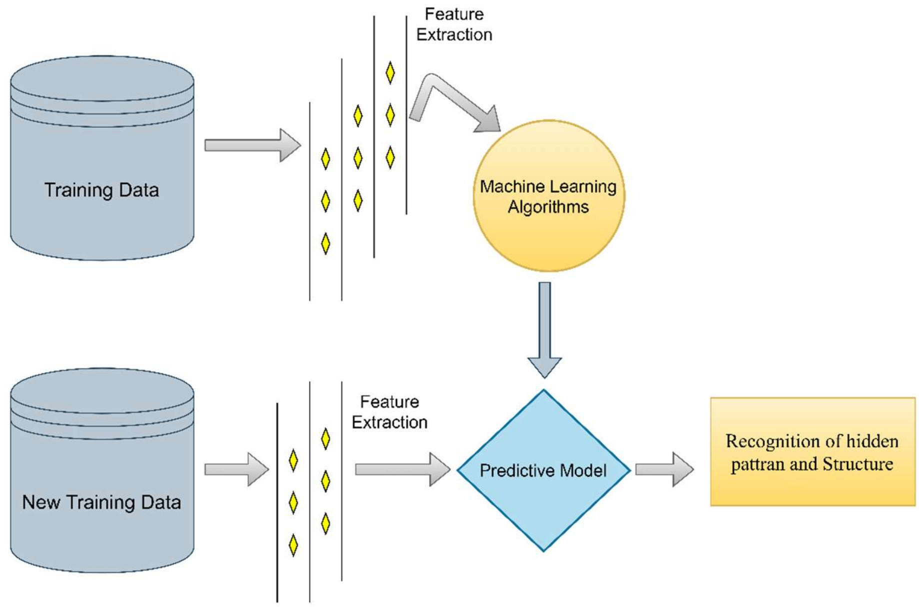

Figure 1. 4 Unsupervised machine learning process

Reinforcement learning: This classification of machine learning is becoming important these days. A computer program dynamically interacts with its environment. This means that the program receives positive and/or negative feedback to maximize a reward [28].

1.2 Role of Education

Education equips to successfully navigate social situations. The personality of an individual is shaped by their family, their education, and their social life. Since humans are social creatures, having a social life is paramount [29]. Education is always a source of the finest chances available. The way people communicate and interact with one another has been significantly altered owing to the intervention of digital technology [30]. Even the method by which information is seen has already changed. The education framework, along with many other sectors, is directly utilizing these developments to get the advantages of ever-changing technologies. The use of artificial intelligence (AI) in education provides a wide range of options, including the ability to grade assignments and track learners' progress [31]. Education is said to provide the foundation for better careers. Students identify job titles as per the courses applied and completed. Different streams offer various job opportunities [32]. Better education gives self-confidence to work. Confidence to care for people with mental health problems can now be addressed within education [33]. Education affects the economic growth of a country as well. Education is also playing a role in promoting economic well-being. Quality education also focuses on and relates to individual earnings, the distribution of income, and economic growth rather than just focusing on school attainment [34].

1.3 Category of Education

Education helps to differentiate between right and wrong. The three types of education are formal, informal, and non-formal, respectively.

1.3.1 Informal Education

In an informal education, knowledge can be grasped from any sources like books, TV, radio, libraries, videos, educational websites, and other sources. Students are independent and to study from any source at any time. There is no fixed timetable for it. No formal degree is provided to the students under informal education. For young people, especially those leaving the foster care system, informal mentoring, a naturally forming loving connection with a non-parental adult, has been found to enhance beneficial outcomes. Even though it frequently describes mentoring as a uniform experience, new research has shown that mentors differ significantly in terms of both who they are and the kind of assistance they provide [35] [36].

1.3.2 Non-Formal Education

Non-formal education is imparted for job skills and other basic skills. This is imparted very consciously. It can be provided by individual teachers or institutes. Age is not a limit for non-formal education. Certification may or may not be provided [37]. Learning outcomes and education are closely related. The skills and information that students must possess after completing the course are essentially the prime intent. The focus of learning outcomes is not on how much content is taught, but rather on how knowledge is used and integrated [38]. In non-formal education, children and teens can have fun in three different ways: through the activities they are working on, socially by sharing with other participants, and pedagogically through the enjoyment that is included in the learning process. It is advised that amusing components be used in non-formal technology education to increase the participants' motivation and engagement [39].

1.3.3 Formal Education

Formal education is one in which a student gets into the premises of an academic institute. Teachers and students participate in the educational process here. The planned education process is followed through structured deliberations. A well-defined syllabus is designed and attendance during the content delivery is regulated. Trained teachers provide knowledge to the students. After the course has been completed, the students receive an encased document upon completing the requirements. According to research, formal education and literacy do not affect the arrangement of semantic categories or the fundamental access mechanisms to them, but they do influence the depth and accuracy of conceptual understanding.

Fluency analysis took into account overall performance, sequential order, and reaction time. Even with the poorer performance, those with higher levels of formal education, illiterates, and adults with little to no formal education displayed systematic grouping and extraction by useful subcategories [40].

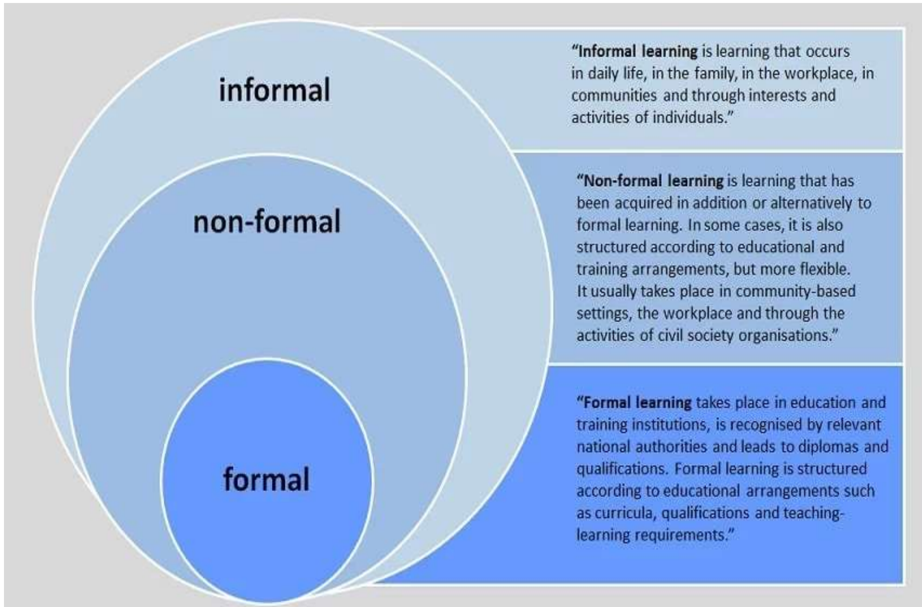

Figure 1. 5 Categories of Education

Figure 1. 5 represents the three categories of education i.e. formal, non-formal, and informal.

1.4 Foundation of Proposed Work

Education plays an essential part in society for the upliftment of an individual and society by and large. A correct, effective, and intelligent platform for assessment plays a primordial role in education. The proposed work addresses academic tenet. The proposed study will provide a mechanism for all stakeholders in the public or Govt. Sector related to education for truthful assessment of learning outcomes of a course based on micro parameters of lecture-wise and unit-wise real-time measure. The proposed research topic produces new knowledge in the concerned discipline as this research proposes to produce a novel idea to measure and map student learning. Through this work, an intelligent self-learning system is proposed to measure how much learning outcomes are attained. The traditional approach for improving learning outcomes is to alter the pedagogy and evaluation standards, but this novel idea combines academic emotions with direct assessment, in which students are evaluated based on the grades they receive on tests, midterm exams, and end-of-term exams, among other parameters.

1.5 Central Theme

- **Assessment**: It is the measure of how much attainment of the outcome has been achieved.
- **Course Learning Outcomes:** It is a well-described point-wise knowledge, skill, and aptitudes that a particular course is designed to imbibe in the learner.
- **Mapping:** Mapping is the process of describing the association between the parameters, ideally in matrix form. Quantitative Measure of Learning Outcomes: Based on the performance of students through assessment tools.
- Qualitative Measure of learning outcomes: Based on student's perception of deliberations in the class rated by students on a five-point scale.
- **Collating**: Enjoining and co-analyzing qualitative and qualitative measures of outcomes.

1.6 Types of Assessment

In the National Board of Accreditation (NBA) report entitled "**3.3.3 Criterion 3- Course Outcomes and Program Outcomes**" and In the National Board of Accreditation (NBA) report, criterion 3, based on "**Course Outcomes (CO) and Program Outcomes (PO)**", in section 3.3.3 it is described that the program must explicitly explain the forms of course delivery, how evaluation techniques are utilized to measure the effect of course delivery/content, and how laboratory and project work contributes to the achievement of the course outcomes (COs) and Program Outcomes (POs). Assessment can be done directly or indirectly.

- **Direct:** Direct assessment belongs to the observation of pupils' knowledge or abilities against quantitative performance markers and is the most common type of evaluation.
- **Indirect:** Ascertaining opinions and feedback from various stakeholders are used as an indirect means of assessment.

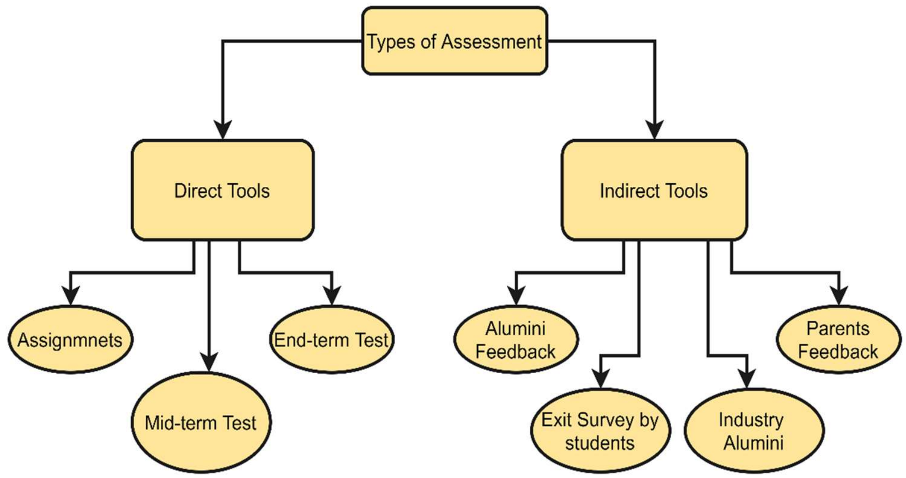

Figure 1. 6 Types of Assessment

1.7 Significance of Student Learning Outcomes

Any educational institution prioritizes the attainment of learning outcomes for its students. Student learning may be measured by what students understand and can do after finishing a certain course. Now in the 21st century students choose courses according to their personal choice along with mandatory courses desired by the scheme. Through the learning outcome of a course, students can judge what course to choose. Students prefer to scrutinize the course or program outcome before registering for a course and this can assist students in selecting the best course for their needs.

Learning outcomes should be based on four factors.

- Knowledge
- Cognitive skills
- Practical skills
- Generic skills

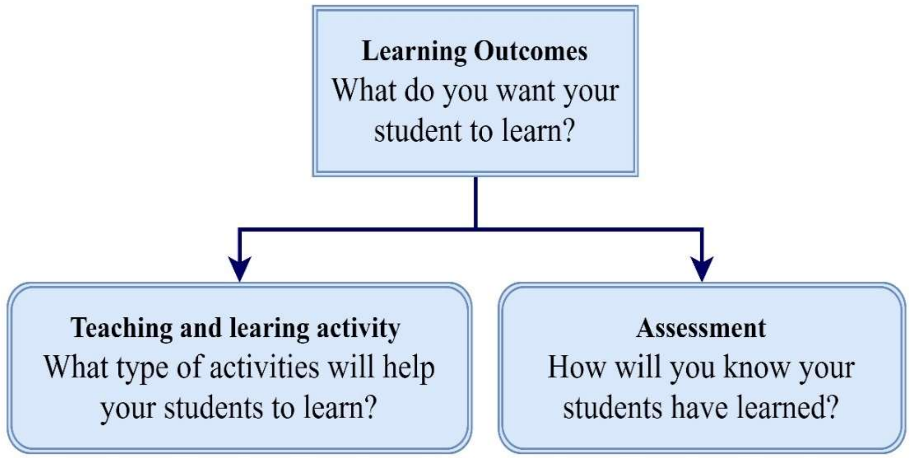

Figure 1. 7 Significance of student learning outcomes

Figure 1. 7 depicts the process of student learning outcomes that includes the teaching-learning activities and evaluation of the students. The results of learning reflect what students should know after completing a course, as per the teacher's point of view. Learning activities involved in the curriculum help students to achieve learning outcomes. Finally, the evaluation of the students clears the actual learning of the student [41].

1.8 Thesis Organization

The thesis structure and flow are discussed in this section chapter-wise. Chapter 1 focuses on the existing education systems representing the needs and benefits of the education system, the significance of student learning outcomes, and the need to capture students learning outcomes on a real-time basis. Chapter 2 focuses on the existing system and assessment of learning outcomes. This chapter presents various mechanisms used for learning outcomes, aggregation model, and machine learning-based model. Chapter 3 elaborates on comparative analysis based on evaluation mechanisms and technology. Chapter 4 explains the development of the TERE framework for capturing real-time student learning and academic emotions. Chapter 5 focuses on building an aggregation model to enjoin qualitative and quantitative learning of the students. The sixth chapter focuses on the accurate evaluation of learning outcomes based on micro to macro characteristics. Chapter 7 consists of the conclusion of the research accomplished.

1.9 Summary

Education is an important and primary need of life. A variety of colleges and universities will create a new generation of people who can organize their futures in a developing economy. Assessment is essential for tracking development, choosing the next steps, and reporting. This includes parents, students other stakeholders, and teens in the learning process. It has been analyzed that most of the education systems are using only quantitative aspects of education and this system has several limitations on reporting the truthful measure of learning among the students. This results in a lack of engagement among the students. Considering only the quantitative side of student learning assessment may lead to ambiguity. The qualitative measure is the new form that needs to be considered along with quantitative measures. This can fill the gap in the present teaching-learning process. The assessment that includes both qualitative and quantitative measures of education will prove to be a more authoritative gauge of learning.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Introduction

This chapter contains a comprehensive literature review pertaining to the analysis of the education system specific to student learning outcomes. The literature review is divided based on objectives. First, the literature on assessing learning outcomes is reviewed. Further, various research on aggregation models have been presented. Finally, related work to develop a framework has been deliberated. The literatures based on objectives are enumerated in the following subsections:

2.2 Assessment of learning outcomes

Engineers are the ones who ideate and build solutions to real-life challenges. Engineering curriculum includes science and technology, mathematics, etc. So, teaching and learning have become tricky these days, especially in engineering courses. The reason for this is primarily the shortage of teachers, insufficient infrastructure and laboratories, etc. [42]. There are many resources for education available such as

2.2.1 Massive open online courses (MOOCs)

MOOCs are a great resource for education. The workplace quickly adapts to MOOCs. However, there is a lack of systematic research through MOOCs on learning and teaching dynamics. The Past showed that the focus was on trends and technologies of MOOCs. According to observations, the majority of MOOC participants were highly qualified as compared to less educated learners. Evidence-based research on MOOCs is less on non-mainstream consumers, the learner factor is over simple, and learner engagement is not tallied using various approaches [43].

2.2.2 Academic Accreditation

To understand how technology affects students' learning, it is vital to look at the components that influence an institution's accreditation process. Academic accreditation standards focus on student assessment including learning outcomes. Nowadays every university focuses on getting the privilege of accreditation from accrediting bodies. The main idea of student learning, teacher technology experience, and university performance in academics comes from the general criterion of accreditation standards. Each university has evaluation and assessment criteria. These criteria convey many things like student achievement, teacher's experience, and technology having effects on the university's outcome as a whole.

2.2.3 Blended Learning

The blended learning method is where learners use digital and internet resources, as well as conventional face-to-face teaching, to get better academic insights [44]. The usage of technology will lessen global issues like space, etc. However, putting online learning into practice is also a difficult task. Online learning combined with a virtual community has merged student involvement and learning outcomes. This will encourage students' learning outcomes. Today's use of cloud computing makes it easy to adapt online learning [45].

2.2.4 Online Interactions

Online interactions are being used more often in official and informal learning settings whereas online interaction is considered a knowledge-construction process. Knowledge construction is related to learning outcomes by formal assessment. Focus should be given to the community as a whole to understand the characteristics for better learning interactions [46].

2.2.5 Exploring the diversity in student learning

An approach needs to be followed i.e. what is learned rather than how much is learned for measuring learning outcomes. Different strategies and processes are used to check learning outcomes. The learning outcome is examined by what is understood and captured. Levels of learning outcome vary from surface learner to deeper level based on the engagement of the learner in content. It is pointed out that learning outcome is a qualitative reflection of course i.e., whether students perceived the thing in the same way or not. The first aim was to find the qualitative difference in learning outcomes. Various concepts or principles were understood by different students in different ways.

Exploring the diversity in student learning outcomes can lead to various ideas and information that will help in teaching [47].

2.2.6 Cybernetic Method

The cybernetic method has been used to encourage learning strategies. In a novel learning environment, it is necessary to regulate the studies to achieve their goals. The cybernetic baseline method resulted in specific outcomes and it also manages various disturbances by using a regularity mechanism. It is suggested that adding cognitive strategy to the curriculum increases the student's regularity and improves academic achievement [48].

2.2.7 Motivation and learning techniques

Student learning results are improved when motivation and learning techniques are explored together. Additionally, it aims to find out from students what difficulties they anticipate having with learning tactics and motivation. Some Recommendations are also suggested as the teacher can ask for assistance from the student's time to time. Teachers should correlate motivational beliefs with students' instruction strategies. So that students can value motivational beliefs and integrate them with their study benefits. Evaluation of students should not be purely based on grades. It should include the skill and talent of the student. The Ministry of Education should train all the teachers, and school mentors so that they remain motivated and focused on academics. Parents should also support their children to study at home [49].

2.2.8 Systematic Review

Moreover, systematic review for the betterment of education is to inventing policies. Findings suggested that obstruction is better for educational improvement and for that two or more drivers should be combined to get the desired result in education policy. The first driver can change the supply side i.e. providing extra material, teachers, and physical things. The second driver focused on the relationship between the supply side and demand side which influence behavioral, student, and inter-temporal teacher choices. The third one shows the change in terms of top-down and bottom-up approaches to participatory and community management strategies. It's better to add social norms and choices of the teacher to independently make decisions of what and how much to do at a particular point in time under education policy. For the educational policies, experimental and quasi-experimental policies need to be viewed [50].

2.2.9 Learning Partnership

One more term is used in learning i.e. partnership in learning. Here partnership means that the student is learning by teaching. Here, students get the chance to experience learning by teaching. After an interview, it was experienced that students who got a chance to learn by teaching have more assessment literacy and deep learning as compared to the students who do not get the chance to partnership learning. Results also show that students get a better and deeper understanding of the topic if they teach another student. Partnership learning also increases the knowledge about the assessment of the student and gives the student a lifelong learning experience by teaching [51].

2.2.10 Focus on learning behavior

University students learning behavior and skill development were examined by applying Expectation Disconfirmation Theory (EDT) to one domain of the learning commons. To improve teaching and learning outcomes, learning commons emphasize creativity, cooperation, innovation, and opportunity. Learning Commons encourages participatory learning. Learning commons affects the perceived quality of degree along with student satisfaction. Further, it will lead to psychological outcomes. It will reflect the changes in the student’s grades, problem-solving skills, and improved learning outcomes. It will also result in saving student’s time and reduce effort to work. Expectation disconfirmation theory can be applied to various fields to see its effect on student satisfaction. Analysis has shown a strong relationship between Educational Development Targets (EDT) and learning common. Students already set their expectations from this theory if it will show a positive relationship, then students feel highly motivated. If students do not get good output then they feel disappointed. But for all this Learning commons quality and student satisfaction should be planned properly [52].

2.2.11 Quality Assurance

In the 21st century education quality and quality assurance play vital roles in higher education. Student learning outcomes a proof of the educational quality that has been provided by an educational institute. In an educational institute, students are the main asset to be focused on. The Council for Higher Education Accreditation (CHEA) International Quality Group (CIQG) is going to explore new quality assurance standards i.e. Student learning experience (SLE) and value-added learning. Student learning is not a one-day process it is an enduring process. The student learning process can be improved by analysis of the student learning process continuously [53]. A new idea is also presented i.e. assessment for learners. In previous times assessment was done from time to time. However, a new framework comes with how assessment makes learning better. So, the quality of the assessment is determined by factors like human judgment and psychometric methods. The main motive is to change awareness of assessment. During the assessment, if some points are found irrelevant then they can be omitted [54]. The impacts of assessments on learning, fair assessments, circumstances of assessments, test result interpretation, authenticity of assessments, and credibility of assessments were six significant factors connected to students' perspectives. In terms of deep learning and strategic learning approaches, student perception is positively correlated with assessment's impact on learning [55].

2.2.12 Learning Engagement

The importance of learning engagement has been shown in academic achievement. Currently, teacher reports and classroom observation methods are used to see student engagement. A novel design of assessment is used where a child's engagement has been seen in the laboratory. Six factors are composed of behavioral engagement attention to instructions, on-task behavior, zeal, persistence, strategy use, and negative effect. The new measure established will help researchers in laboratory assessment by concentrating on resources [56]. Some studies have shown the relation between mobile games-based learning and student learning outcomes. Students benefit from game-based learning in high school [57].

2.2.13 Collaborative Learning

The use of mobile devices and collaborative learning in education has been used in education. Collaborative learning can be used either with mobile or without mobile. Students like to work in groups by using mobile tools but it can give rise to distraction in the class. Additionally, using tools to create written responses rather than making responses on mobile devices will help students' critical thinking skills develop more. Student’s engagement in a particular assignment can be identified by their speech, sitting posture, eye contact, etc. If students are not engaged in the assignment then it is reflected through not making eye contact, different body language and gestures, etc. Engagement of students is increasing with the use of mobile tools and distraction too. Results suggested that different tools can be used in the classroom for students to serve the purpose of engagement. But at the same time tools must contain basic functions required by the students [58]. As per the latest empirical studies, young students, infants, and children use cross-situational learning to study new words, and statistical information can be used by learners for learning word object mappings from multiple data sources. One crucial item to remember, in the context of real life, real-time behaviors play an important role in investigating early language development. Better student learning results can also be attributed to cognitive traits. One such factor is the disfluency effect. It is mentioned that the change in notes will obstruct to perception effect and finally result in better student learning outcomes [59].

2.2.14 Flipped Classroom Learning

The level of satisfaction of the student remains the same in either a flipped classroom or a non-flipped classroom. However, students achieve higher learning outcomes as compared to the non-flipped classroom when direct time in a flipped classroom is not compact as compared to the non-flipped class. The classroom method is an effective instructional method but it needs to be designed properly by including quizzes etc. [60]. Nowadays, students would like to use smart devices to solve their technical problems. Implementation of the Internet of Things (IoT) as an element of flipped class to solve the mathematical/logical course is common. Work on the problem belongs to the course, and can be handled outside the classroom with the Intelligent Tutoring

System used in flipped classes. Flipped classrooms can increase efficiency, compatibility, and usefulness for continuance aims to use flipped classrooms [61].

2.2.15 Role of projects in academics

Projects are very significant in the cognitive, affective, and behavioral learning outcomes of students in many business schools and universities. The framework of international entrepreneurship has been proposed by executing student consultancy projects. This framework also included teaching practices to maximize the achievement of learning outcomes in an international entrepreneurial context in management education. There, is an association between the student learning outcomes, teacher practice, and consultancy process. Academics also play a crucial role in projects and it's important to create a balance between the two. With the involvement of these projects along with academics, students can get better jobs that fulfill the cognitive, affective, and behavioral requirements of employers [62].

Further, Research describes how giving learner's calibration signals affects their capability to self-regulate their learning. Both blended learning and calibration support students' self-regulation separately. Further, it is investigated whether self-regulating learning is different for learners with changed meta-cognitive abilities. Effects can be explored with Changes in learner's behavior and learning outcomes. Students' learning results and behavior are significantly influenced by their metacognitive learning. Calibration capabilities of the learner, cognitive validity feedback will be boosted when cues for calibration are provided [63]. Focus is given to deaf student's progress and interaction by developing an adaptive e-learning system. To enhance hearing-impaired students' interaction and progress bilingual/bicultural, adaptive learning, and mobile technologies are used. The basic language used by these students is sign language. Academic Advisor Agent evaluates their Learning Outcomes results. An academic advisor helps deaf students to achieve better program outcomes. Academic advisor guides deaf students to achieve Deaf Students Learning Outcomes (DSLO) levels. Academic advisor mainly focuses on learning obstacles, lecture assessment, and proposing learning activities, etc., Methodology has adaptive reading, adaptive questions along with text images and sign videos [64].

2.3 Literature around Aggregation model

A new methodological approach for evaluation criteria for quality assessment has been suggested which is based on aggregated time series. Peak-load-pricing model is derived from analytical results for a basic problem. In analytical calculus, aggregation methods are the first step in developing time series. In the future, for more complex problems additional aggregation and development rules can be developed [65]. Further, an aggregation model based on evidence theory has been presented in this study. Generally, Multisource Assessment (MSA) is comprehended by using the averaging method. This system has been verified by using many conditions and it was found that it gave more accurate results in the MSA model. Here different methods and evidence combinations for different conditions to give aggregate results have been used [66]. The difference in the expert opinion is the most important factor in differentiating aggregation modes. Sometimes it combines first and then circulates and some other times first circulates and then combines. To measure disagreement in an expert's opinion Divergence Metric is proposed. The aggregation rule used is Cumulative Distribution Averaging. This is an appropriate rule for both probabilistic and non-probabilistic opinions. One more factor influencing the difference between aggregation modes is the operating point in the probabilistic space for the propagation model. Results show that the more conservative mode is aggregation before propagation than aggregation after propagation [67].

The aggregation has been seen on many parameters in education like metaverse, and information, model application and domain of application. The concept of integrated learning, mixed method approach, etc. has been incorporated under the aggregation model [68] [69] [70]. Aggregation algorithms are critical in the federated learning process as they integrate the information of multiple clients locally and combine to train a global model [71]. Nowadays, by exploring student learning by modeling unstructured data, the research pays to the rising attention to K-12 AI teaching [72]. Aggregation of Qualitative and Quantitative feedback represents the mixed method assessment [73] [74]. In the same way, the proposed intelligent mechanism includes various algorithms and provides better results.

2.4 Summary of Aggregation Model

A summary of the aggregation model is given in Table 2. 1.

Table 2. 1 Summary of aggregation Model

Sr. No.	Paper Title	Author Name	Contribution	Parameters
1	Model aggregation techniques in federated learning: A comprehensive survey	P. Qi, D. Chiaro, A. Guzzo, M. Ianni, G. Fortino, and F. Piccialli (2023)	Examining the connection between model aggregation and application domains. Identification of federated learning difficulties, such as bottlenecks and privacy/security.	Model aggregation in federated learning.
2	Reviewing Federated Learning Aggregation Algorithms; Strategies, Contributions, Limitations and Future Perspectives	M. Moshawrab, M. Adda, A. Bouzouane, H. Ibrahim, and A. Raad (2023)	Aggregation algorithms are essential in the federated learning process. This paper discusses various federated learning aggregation	Distributed machine learning and aggregation algorithms.

Sr. No.	Paper Title	Author Name	Contribution	Parameters
			methodologies and algorithms.	
3	An empirical analysis of high school students' practices of modelling with unstructured data	S. Jiang et al., (2022)	This research contributes to knowledge of how students learn to model real-world data and has implications for enabling in-depth model decision-making.	Qualitative analysis, AI.
4	Metaverse system adoption in education: a systematic literature review	R. Alfaisal, H. Hashim, and U. H. Azizan (2022)	The findings are expected to considerably improve both our understanding of metaverse system studies and the use of information system models.	Metaverse and information system.
5	Affective recommender systems in the educational field. A systematic	C. Salazar, J. Aguilar, J. Monsalve-Pulido and E. Montoya (2021)	A framework based on integrated learning analytics was developed.	An integrated learning analytics framework was Developed.

Sr. No.	Paper Title	Author Name	Contribution	Parameters
	literature review			
6	Challenges in real-life emotion annotation and machine learning based detection	L. Devillers, L. Vidrascu, and L. Lamel (2021)	It is essential to be acquainted with the outcome-based education system. A mixed-method technique is used to acquire qualitative and quantitative data.	Mixed Method approach.
7	Time series aggregation – A new methodological approach using the "peak-load-pricing" model	A. Pöstges et al., (2019).	A new methodological strategy is suggested for the evaluation standard for solutions for quality assessments. Aggregated time series are the foundation of the solution.	Important demand indicators include the following: yearly electricity demand, hourly demand (max/min), annual residual load, and hourly maximum and minimum residual load. Minimum/maximum generation of renewable energy per hour.
8	Data aggregation in	H. N. Titkanloo et	A new aggregation	DRC, conjunctive and Disjunctive

Sr. No.	Paper Title	Author Name	Contribution	Parameters
	multi-source assessment model based on evidence theory	al., (2019).	model based on evidence theory. The proposed model applies different methods, and evidence combinations for different conditions.	combination rules.
9	A comparison between aggregation before and after propagation based on a reliability model	M. Berdai et al., (2018).	The difference in aggregation modes is explored in the proposed study.	The aggregation rule, the gap between expert opinions, and the propagation model selects theories for representing expert opinions.
10	Evaluation of Web-Based Continuing Professional Development Courses: Aggregate Mixed-Methods Model	A. Onan and S. Korukoğlu (2017)	An aggregate mixed-methods assessment model has been created to characterize the paradigm and theoretical framework.	Inductive and deductive methodologies have been employed for qualitative feedback, and for quantitative analysis, dependent samples t-tests have been used.

Sr. No.	Paper Title	Author Name	Contribution	Parameters
11	A feature selection model based on genetic rank aggregation for text sentiment classification	Ebn Ahmady, M. Barker, M. Fahim, R. Dragonetti, and P. Selby (2016)	An ensemble feature selection method that combines different feature lists provided by several feature selection methods to generate a more resilient and productive feature subset.	Utilization of Experimental evaluations and Genetic algorithm.

2.5 Literature on developing a machine learning-based model

Student engagement and active application are improved when an intelligent system is used in the classroom. Education benefits greatly from artificial intelligence tools like educational data mining, learning analytics, and knowledge. The main objective is to see the benefit of using the intelligent system method by collecting expert opinions from intelligent information access systems. Results show that interviewees are less aware of the terms like intelligent system. However, an understanding of the probable utility of the BioAnnote, CLEiM, and MedCMap systems is there. According to this work integration of active learning and Intelligent Information Access (IIA) can be helpful but during development, some key themes need to be considered [75]. The way people communicate and interact with one another has altered as a result of digital technology. Even the method by which information is seen has already altered. The education sector is immediately implementing these changes to reap the benefits of artificial intelligence technologies, along with many other industries. Many opportunities can be provided with the implementation of AI like assignment assessment and measuring learning progress. Technologies help in education with assessment and compilation. Technology provides an opportunity for better student feedback and monitoring. When Intelligent Tutorial Systems (ITS) are used in the classroom, feedback and monitoring outcomes outperform those of traditional classrooms. ITS acts somewhat like a teacher however, it is important to remember the relationship between working with AI and Actual Teachers [76].

The efficiency of the firms is analyzed with an interpretable machine learning model. Changes and growth are captured over time for these firms. Impact factors of innovations are figured out by models like linear regression, decision trees, random forests, neural networks, and XGBoost models. The future innovation performance of a particular firm can be derived from the current state by using the XGBoost model. The cluster of firms is made based on the size of the firm. This model can help organizations to make predictions about their innovations. Furthermore, a decision support system may be constructed to deal with the firms' difficult decisions. This approach is also useful in project assessment when deciding which project to pursue with limited funds [77]. In this paper, the best-worst method finds the optimal weight for a multi-criteria decision-making method based on the preferences of only one decision-maker. Here Bayesian Best-Worst Method (BWM) group of Decision Makers (DMs) comes across aggregate weights of criteria at once. Weights are calculated in attendance of a group of DMs in the Bayesian hierarchical Model. Creedal ranking is introduced to measure DM preference criterion one over another by assigning a confidence level to each criterion [78].

When students study the circulatory system using Meta Tutor, the emotions of the students, whether good or negative, are examined. Evidence score of emotion is calculated when students are busy in cognitive and metacognitive, self-regulating learning. The overall learning as well as emotion scores based on computed scores have been examined. The result indicated positive and negative predictions of cognitive strategies. Frustration results in a positive prediction of cognitive learning strategy whereas surprise score results in a negative prediction of meta-cognitive judgment. Study indicates that negative emotion plays a positive role in advanced learning technology [79].

The National Hockey League (NHL), which brings in significant money in North America, is an expert system suggested to forecast NHL results more accurately. This system helps in better recruitment as well as better salary decisions. Some of the approaches that may be used to predict whether a team will win a game are principal components analysis, nonparametric statistical analysis, a support vector machine, and ensemble machine learning. Comparison of various approaches applied to ensemble machine learning provides an opportunity for improved prediction about the game's accuracy. This research proposed an expert system to predict the chances of winning the NHL. Data is collected from various sources. This system provides accurate results by using big data and machine learning about the game win [80].

The present approaches for gathering, analyzing, and reporting data on learners have been examined using learning analytics. Although there are techniques for it, in higher education, emphasized students are not identified at an early stage. A prediction model for defining student attendance in descriptive statistics is created using machine learning technologies. In the first three weeks after the start of the semester, this model aids in locating the anxious student. By using the right pedagogy, this model may be utilized as a student support system. The issue of student retention is addressed in this work through machine learning. To recognize troubled kids early on, a combination of classifiers is used. The model is dynamic owing to machine learning technologies. Old data is subtracted from and fresh data is added for training [81]. AI has a great influence on education like benefits and challenges etc. AI will open new consequences in the future of educational institutes. Moreover, it will help in handling data more conveniently [82] [83] [84] [85] [86] [87] [88] [89] [90] [91] [92].

2.6 Summary of Machine Learning Model

A summary based on machine learning models is described in Table 2. 2.

Table 2. 2 Summary of an AI-based application.

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
1	New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution	F. Kamalov, D. Santandreu Calonge, and I. Gurrib (2023)	This study will look at the possible influence of AI on education by reviewing and analyzing current literature on three primary axes: applications, benefits, and obstacles.	Deep Learning
2	Enhancing Education Performance through Machine Learning: A Study of Student Learning Outcomes Prediction Using GANs and ANNs	M. Zhong and Z. Li (2023)	In the educational process, there is a lack of uniformity in the execution of policies and the logic of classroom instruction. This study suggests that machine learning models be used to improve the present teaching	Models of Adversarial Network (GAN) and Artificial Neural Network (ANN).

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
			framework.	
3	Shaping the Future of Education: Exploring the Potential and Consequences of AI and ChatGPT in Educational Settings	S. Grassini (2023)	This study intends to dive into issues, examining and challenges of using advanced AI models in education e.g. adoption of Generative Pre-trained Transformers (GPT), particularly OpenAI's ChatGPT.	AI
4	Artificial Intelligence in Education and Schools	A. Gocen and F. Aydemir (2022)	The goal of this research is to look at what conceivable scenarios exist with the entrance of AI in education and what sort of consequences it might disclose about the future of schools.	AI

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
5	Real-time prediction of science student learning outcomes using machine learning classification of hemodynamics during virtual reality and online learning sessions.	R. Lamb, K. Neumann, and K. A. Linder (2022)	The purpose of this research is to explore how neurocognitive data collected by functional near-infrared spectroscopy (FNIRS) may be exploited to develop prediction models of student outcomes with higher speed and accuracy.	AI
6	Applying machine learning technologies to explore students' learning features and performance prediction	Y.-S. Su, Y.-D. Lin, and T.-Q. Liu (2022)	This study analyzes data from interactive learning environments using machine learning technology and then predicts students' learning results.	Machine Learning
7	The impact of artificial intelligence on	K. Seo, J. Tang, I. Roll,	These findings have impacts on AI system design	AI

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
	learner–instructor interaction in online learning	S. Fels, and D. Yoon, (2021)	in terms of explainability, and careful data collecting and presentation.	
8	Study on Accuracy Metrics for Evaluating the Predictions of Damage Locations in Deep Piles Using Artificial Neural Networks with Acoustic Emission Data	A. Jierula, S. Wang, T.-M. OH, and P. Wang (2021)	For predicting damage locations in deep piles, the dataset from the pile body-installed sensors group achieved the highest accuracy.	Artificial neural network.
9	Machine Learning: Algorithms, Real-World Applications and Research Directions	I. H. Sarker (2021)	IoT is seen as a major frontier that has the potential to improve practically all aspects of our lives, including governance, smart homes, education, communication, conveyance, marketing,	IoT

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
			agriculture, well-being care, business, and many others.	
10	Optimization of machine learning algorithm of emotion recognition in terms of human facial expressions	E. Ivanova and G. Borzunov (2020)	Machine learning algorithms can be used to optimize the various emotions of the students.	Neural network-based methods.
11	Bayesian best-worst method: A probabilistic group decision-making model	M. Mohammadi et al., (2019).	In the proposed study, the Bayesian best-worst approach was used for data aggregation.	AHP method is used for comparison, Bayesian best-worst method, and credal ranking.
12	How are students' emotions related to the accuracy of cognitive and meta-cognitive processes during learning with an intelligent tutoring system?	M. Taub et al., (2019)	When students study the circulatory system using Meta Tutor, their emotions are rated either positively or negatively.	Joy, dissatisfaction, anger, fury, confusion and violence.
13	A Game-Predicting Expert	W. Gu et al.,	To forecast improved	Big data and machine

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
	System Using Big Data and Machine Learning	(2019).	outcomes from the National Hockey League in terms of pay and recruiting, an expert method is suggested. Big data and machine learning are both used by this system to include an expert system.	learning.
14	Utilizing early engagement And machine learning to Predict student outcomes.	C. C. Gray et al., (2019).	Learners' data is now collected, analyzed, and reported using a variety of methodologies and metrics, which are examined using learning analytics.	Classifier selection, Feature selection
15	Application of interpretable machine learning models for the intelligent decision	Y. Li et al., (2018)	This analysis selects the project with the least amount of investment after analyzing the corporate	Cluster type, ownership, industry, company size, and firm age.

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
			efficiency.	
16	Perceptions of the use of intelligent Information access systems in university-level active learning activities among teacher of biomedical Subjects.	F. Aparicio et al., (2018)	Student engagement is increased in the classroom using an intelligent system. For this goal, artificial intelligence methods are applied.	There are several methods employed, including surveys, semi-structured interviews, educational data mining, and learning analytics.
17	Artificial Intelligence trends in education: a narrative overview	M. Chassignol et al., (2018)	The way people communicate and interact with one another has changed as a result of the usage of digital technologies. To gain from artificial technology, even the education sector is directly implementing these changes.	Content, Teaching, methods, Assessment, Communication.

Sr. No	Paper Title	Author Name/ (Year)	Contribution	Parameters
18	Review of computer-based assessment for learning in elementary and secondary education	V. J. Shute and S. Rahimi (2017)	In elementary and secondary education, computer-based assessment for learning has been seen as a realistic technique to combine instruction with evaluation of students' increasing abilities.	Artificial Intelligence
19	Cognitive computing in education	M. Coccoli, P. Maresca, and L. Stanganelli (2016)	Applying AI technologies results in enhancement in the field of education	Artificial Intelligence

2.7 Challenges

Currently, teacher reports and classroom observation methods are used to see student engagement. The major problem identified is that most of the educational institutions used marks only to measure the commitment and learning outcomes attained by the students, which is probably not a true measure. Academic emotions of the students also play an imperative role in students' overall growth. The biggest challenge is to consider both aspects of education i.e. academic and emotional, where academic measures are known as quantitative measures based on the marks of the students and academic emotions represent the qualitative measure of participative learning. It is critical to bring both aspects of student learning together. Literature about the aggregation model shows the idea and scope of collating two or more models.

2.8 Research Gap

- In the modern era, the academic assessment of students is very important to bridge the gap between the student's learning and the outcome achieved in terms of academic performance. Thus, developing a framework that qualitatively measures performance is much required.
- To make the overall system functional data plays an important role. In student assessment, there should be a method where data needs to be collected in real-time. This will give fair data for assessing the student's general participation and learning characteristics. Creating a tool that captures real-time data is one of the important aspects of measuring learning outcomes.
- A stakeholder always expects that conclusive remarks should be presented for a given set of problems. Thus, after getting real-time data it is always expected to draw inferences out of the gathered data and should be presented in graphical mode for better understanding.
- It requires an ever-evolving means to be devised for gaps in the translation of learning outcomes of a course and through data capture and analytics.

2.9 Research Objectives

Student learning outcome plays a pivotal role in the educational ecosystem. To gauge whether a student has perceived the course content aptly learning outcomes need to be assessed. The main objective of this study is to explore various mechanisms presently available for the evaluation and assessment of student learning outcomes. Lecture-wise student learning outcomes are assessed in real-time and aggregated to find out the course-wise learning outcomes. Then qualitative and quantitative measures of learning are combined to get the overall attainment of the student. Multiple outcomes in a lecture are gauged. Then after summing up the entire unit's course wise learning outcome can be reached. Through this work, an intelligent self-learning system is proposed to measure how much learning outcomes are translated.

- To study and compare various mechanisms for assessing the learning outcomes presently being practiced for the identification of gaps.
- To design a real time mechanism for capturing a student learning and their academic emotion.
- To build an aggregation model for summing up lecture wise learning outcome for evaluating unit wise and course wise learning outcomes.
- To propose an intelligent mechanism for truthful assessment of learning outcome of a course based on micro parameters of lecture wise and unit wise learning outcomes attained.

2.10 Methodology

To evaluate student learning outcomes, a conventional mechanism is followed these days which is based on the test or quiz given to a particular set of students. However, assessing the student learning outcome just based on the marks obtained in a particular test is not the only way, as evaluating the learning outcome based on one or two tests before or after midterm is not the only criterion to scale course outcome attainment.

The research is intended to explore more mechanisms if at all being used by any other academic institution for assessing the learning outcomes. Because of this reason, test and quizzes are not the only measures going to explore all other mechanisms that are being used in publications or through various practices being used.

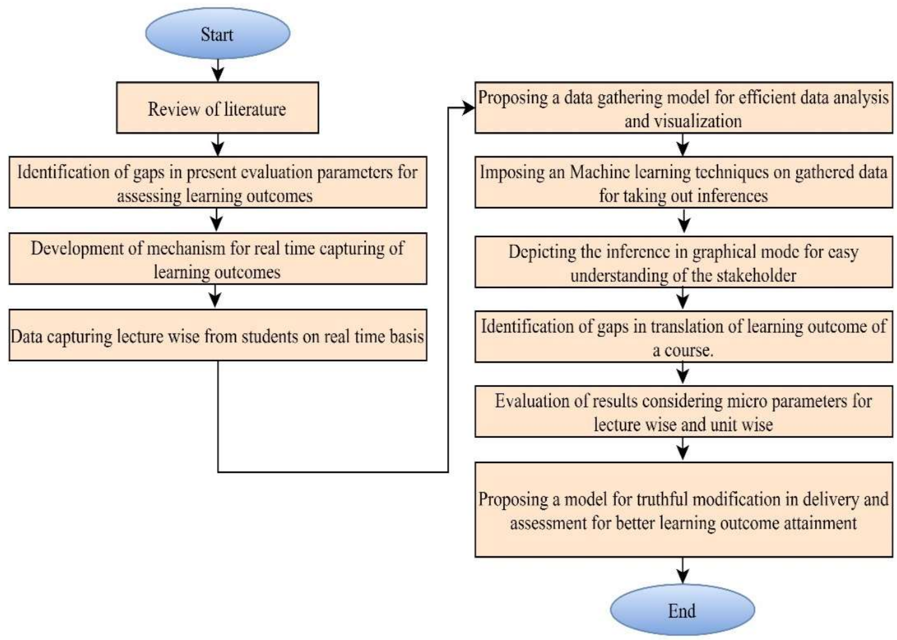

Figure 2. 1 Methodology

The performance of a student is also a qualitative reflection of whether the learning outcome is achieved or not. To find out the truthful course outcome, it is necessary to capture the lecture-wise learning outcomes in real-time. An application is created for a topic discussed in the class during the delivery. Each lecture that is delivered must have an assessment mechanism to measure how much learning outcomes are attained at the micro level. From multiple outcomes in a lecture, it is gauged. Then after summing up the entire unit's course wise learning outcome can be reached. If it is captured without human intervention then an algorithm is proposed that can aggregate lecture-wise outcomes, unit-wise, and finally course-wise outcomes. Finally, the outcome of this work would be an intelligent system that would propose how much learning outcomes are translated based on the mode developed in objective two and what gaps were there.

2.11 Results and Discussions

The literature review includes an assessment of learning outcomes, an aggregation model, and the development of an application using AI and machine learning. Various mechanisms are used in student learning outcomes which include MOOCs, the impact of technology used, mental involvement using games, the concept of a flipped classroom, etc. Moreover, learning environments have a lot of impact on formal and informal education. Parameters like learner factors, learner commitment, teaching context, learning outcomes, learning strategy, motivational beliefs, teacher experience, and technology-enhanced learning impact widely the learning outcomes. AI and machine learning help in the prediction better than other models. In educational institutions, slow and fast learners can be segregated well in advance, or well on time, and maintain student enrollment. Artificial Intelligence and Machine Learning play an important role in education in student assessment, identifying early dropouts, calculating the results, etc.

CHAPTER 3

STUDY AND COMPARE VARIOUS MECHANISMS FOR ASSESSING THE LEARNING OUTCOMES PRESENTLY BEING PRACTICED FOR THE IDENTIFICATION OF GAPS

3.1 Introduction

Education forms the strongest pillar of the societal ecosystem. It carries different meanings to different people. For a student education is a means to acquire knowledge, at the same time for a teacher it is a chance to build a good human being, who can help society by spreading knowledge. For a businessman, education may be a source of earning money [93]. Education provides many benefits to all, which can be at a personal level, social level or monitory level. Education always feeds with the best opportunities around. Education is considered as a base for better careers. Better education gives self-confidence to work and lives in society. Understanding things becomes better with knowledge. Education is a weapon to overcome all worldly problems [94]. Education is like a golden ticket for the growth of a country. Education gives a better lifestyle as educated people participate in all the events actively. It turns life into a more managed and meaningful way to live. Even salary difference comes according to the higher degree. Education affects the economic growth of a country as well. The reason could be either the fee or interest of the student [95]. The future of the students is directed towards the right way with the help of Higher education. The main motive of education is to prepare youngsters to handle future problems in their lives. Along with it, education can help to bring society together. Now, the scenario has changed, education contains relation to learning, ethics, fairness, involvement of the community, the role of research at institutions, etc. [96]. Transformation in education is needed to rethink the education policy. Transformation in learning is required to rethink educational policies and this can happen with the help of academicians and teachers [97].

Education helps to differentiate between right and wrong. Education can be broadly divided into three categories formal, informal, and non-formal. Formal education is one in which a student gets into academia. Teachers and students participate in the educational process here. The planned education process is followed under proper discipline and syllabus. Trained teachers provide knowledge to the students. A degree is awarded to the students after completion of the course. In informal education, students can get knowledge from any sources like books, TV, radio library, and educational websites. Students are independent and to study from any source at any time. There is no fixed timetable for it. No formal degree is provided to the students under informal education. Non-formal education is imparted for job skills and other basic skills. This is imparted very consciously and sincerely. It can be provided by individual teachers or institutes. Age is not a limit for non-formal education. Certification may or may not be provided [98].

Learning outcomes are allied with education. The learning outcome is the skills and knowledge that students must attain after the accomplishment of the course [99]. In the present era, students choose courses according to their personal choice. Students are less dependent on their teachers and parents regarding course choice. Through the learning outcome of a course, students can judge what course to choose. So, it becomes necessary to see the course or program outcome before enrolling. Learning outcomes should be based on four factors knowledge, cognitive skills, practical skills, and generic skills. Learning outcomes can be measured in a long-term course or short-term course. Learning outcomes indicate a perception of the student about the course. Learning outcomes give benefits to both students and teachers. Students get the benefit of choosing an appropriate course judiciously. The teacher can make a proper strategy to deliver and create assessment tools. Teaching material and evaluation criteria can be designed well on time according to the learning outcomes [100].

3.2 Related work

Assessment depends upon more than one evaluation practice like scores achieved in mid-term, end-term, and assignment, feedback, etc. This represents the quantitative measure of learning [101]. In higher education valid feedback and qualitative assessment surely enhance student learning.

Previously, the assessment component was not seen to be the primary emphasis of learning and teaching, but it is now noticeable that the paradigm has changed in favor of assessing students' activities that improve their learning outcomes using AI. The main contribution is given by AI and machine learning techniques in student performance. Various techniques like ANN, XG Boost, Random Forest, and Decision Trees are used to measure the performance metrics [102]. The easiest way to evaluate and support students' learning is to capture feedback on learning outcome parameters i.e. capture students' academic emotions. The role of cognitive and motivational parameters is better understood than emotional assessment. However, academic emotions, along with their feedback, play a significant part in students' learning and must be given the same degree of attention. Emotions are as important in capturing feedback as other parameters like motivation, social factors, cognitive skills, etc. but their role is recently been recognized. Therefore, it is crucial to consider both aspects of education. After going through a detailed literature survey, a gap is identified that in most studies, either quantitative measure is considered or qualitative measure [4][5]. It is essential to be acquainted with the outcome-based education system. To achieve overall achievement, qualitative and quantitative data are collected utilizing a mixed-method technique or an aggregation strategy. It has been seen in existing human behavior studies that emotion has piqued the interest of academics in both computer science and machine learning. To detect important emotional states numerous classification approaches are examined [103]. According to research, making students aware of their emotions and motives can promote self-regulation via technology more effectively [108] [105] [106]. In real-time, the Recommender System evaluates a student's learning productivity and excitement for learning [107]. Emotion parameters are a vital ability that can either benefit or decelerate performance. Positive emotions include the enjoyment of learning, interest, hope, confidence, and empathy for others, which are facilitated by successful emotion regulation [108] [109].

Various parameters which include online learning, emotional and behavioral engagement, digital media and ITC, etc. have been used under various mechanisms [110] [111] [112] [113] [114]. To increase the student's learning and development various parameters like student’s leadership, efficiency, and culture of the school also matter [115]. In the case of health professional education motivation and psychological well-being matter a lot [116]. To improve students' learning outcomes weekly learning outcomes are evaluated. Time management for students plays a crucial role in incorporating research into their studies [117] [118]. To make learning easy various multimedia tools and technology components have been added. Growing class sizes and increasing use of technology lead to adding emotional parameters to the evaluation of the students [119] [120]. Various mechanisms like the learners’ factor are displayed in Table 3. 1.

Table 3. 1 Mechanism used for learning outcomes

Sr. No.	Ref. No.	Paper Title	Author Name /(Year)	Contribution	Parameters
1	[121]	Integrating AIGC into product design ideation teaching: An empirical study on self-efficacy and learning outcomes	K.-L. Huang, Y.-C. Liu, M.-Q. Dong, and C.-C. Lu(2024)	The advent of artificial intelligence-generated content (AIGC) significantly impacts student learning outcomes and self-believe.	AIGC helps to improve the critical thinking of all levels of students. It will help students to generate ideas and solutions.

2	[122]	A meta-analysis of eight factors influencing MOOC-based learning outcomes across the world	Z. Yu, W. Xu, and P. Sukjairungwattana (2024)	MOOCs effect on online education has been lessened due to various factors. Which can be improved in upcoming times.	Factors reducing the effect of MOOCs are behavior intention, learning engagement, students' inspiration, insights, fulfillment, performance, etc.
3	[123]	Evaluating training effectiveness in India: Exploring the relationship between training components, metacognition and learning outcomes	Zahid Hussain Bhat(2023)	This study attempts to investigate the major training components that have a major influence on trainees' learning results.	Here, connections between different training elements, teacher effectiveness, training utility, and their impacts on learning have been observed.
4	[110]	How students view online	C. L. Huang, C. Wu, and S.	Online teaching and learning would benefit from	Online learning along with

		knowledge: Epistemic beliefs, self-regulated learning, and academic misconduct	C. Yang (2023)	research on students' internet-specific epistemology views (ISEB) and their connections.	strategies for teachers, librarians, and schools to improve students' ISEB scores.
5	[111]	Interaction during online classes fosters engagement with learning and self-directed study both in the first and second years of the COVID-19 pandemic.	C. Gherghel, S. Yasuda, and Y. Kita (2023)	Interaction in online classrooms increased self-directed study time.	Engagement in online learning on an emotional and behavioral level.
6	[115]	Working memory training: mechanisms, challenges, and implication	S. Jia, S. MacQuarrie, and A. Hennessey (2023)	This research focuses on the application of working memory training in schools to promote students' learning. Development of	Leadership, self-efficacy, and school culture.

		for the classroom		collaboration between researchers and educators.	
7	[116]	The Effect of Assessments on Student Motivation for Learning and Its Outcomes in Health Professions Education: A Review and Realist Synthesis	R. A. Kusurkar et al., (2023)	This evaluation was guided by how evaluations affect student motivation to study in health professions education, and where it leads.	Motivation and psychological well-being.
8	[112]	Digital Media in Institutional Informal Learning Places: A Systematic Literature Review	M. Degner, S. Moser, and D. Lewalter (2022)	Digital media can significantly improve learning processes. Digital media promote knowledge acquisition, interest, collaboration, and social interaction.	Digital media.

9	[113]	I always take their problem as mine' – understanding the relationship between teacher-student relationships and teacher well-being in crisis contexts	D. Falk, D. Shephard, and M. Mendenhal (2022)	Digital media promote knowledge acquisition, interest, collaboration, and social interaction. Implications for teacher education, ongoing school-based assistance, and future policy research, and practice impro ve great education in environments of violence and forced displacement.	Digital media.
10	[114]	Qualitative social media content analysis as a teaching-learning method in higher education	E. Mora, N. Vila, and I. Küster (2022)	Because of the widespread adoption of information and communication technologies, qualitative research is more important than ever.	Information and Communication Technologies
11	[159]	Teacher support and academic engagement among	M. Sadoughi and S. Y. Hejazi (2021)	Academic procrastination is common among students who are enthusiastic about	Present findings can be extended on the different

		EFL learners: The role of positive academic emotions		their academics.	parameters like populations, and contexts.
12	[117]	Visualizing weekly learning outcomes (VWLO) and the intention to continue using a learning management system (CIU): the role of cognitive absorption and perceived learning self-regulation	D. Al-Shaikhli, L. Jin, A. Porter, and A. Tarczynski (2021)	Visualized Weekly Learning goals (VWLO) were developed in this study as a technique for exposing students to the required learning goals weekly.	To evaluate answers, use the Partial Least Squares Method.
13	[118]	College Students' Time Management: a Self-Regulated	C. A. Wolters and A. C. Brady (2020)	The central premise is that self-regulated learning provides a rich conceptual framework for	Self-regulated learning includes performance and post-

		Learning Perspective		comprehending college students' time management and driving research into its relationship to academic success.	performance stages.
14	[119]	Multimedia tools in the teaching and learning processes: A systematic review	M. D. Abdulrahaman et al., (2020)	This paper conducts an organized examination of various multimedia tools used in teaching and learning processes to investigate how multimedia technologies are shown to be a viable scheme for bridging the gap in providing unrestricted access to quality education and improving student achievement.	Multimedia tools, evaluation methodologies, technology components, etc.
15	[42]	Progress and new directions for teaching and	R. Deng, et al., (2019)	MOOCs offer excellent opportunities for teaching and learning. The workplace can	Learner factor, learner's engagement, teaching context,

		learning in MOOCs		adjust more quickly.	learning outcomes.
16	[57]	Mobile game-based learning in secondary education: Students’ immersion, game activities, team performance and learning outcomes	Huizenga et al., (2019).	This study demonstrates that students are highly mentally engaged in the game, and that particular game behaviors in mobile games have an impact on the game's outcome.	Game activities specific to this mobile game, General game activities, and Off-task behavior.
17	[47]	Students’ perceptions of assessment quality related to their learning approaches and learning outcomes	K. J. Gerritsen-van Leeuwenkamp et al., (2019)	A method for linking students' interpretations of evaluation quality to their learning techniques and learning results has been proposed.	Deep learning approach, Surface learning approach.

18	[60]	The effect of cues for calibration on learners' self-regulated learning through changes in learners' learning behavior and outcomes.	Van laer et al., (2019).	The authors of this study looked at how giving learner's calibration signals influences their ability to self-regulate their learning. Separate studies on self-regulation in students were supported by the literature on blended learning and calibration.	Using a blended learning approach, calibration cues, feedback signals for functional and cognitive validity, Examination of learning behavior, assessment of learning attempts, and evaluation of learning confidence.

19	[45]	Effects of flipping the classroom on learning outcomes and satisfaction: A meta-analysis	D. C. D. van Alten et al., (2019).	The writers of this article employed a meta-analysis together with the idea of flipped classrooms. In this investigation, the learning results in flipped classes and traditional classrooms were compared.	Type of Publication, level of education, academic area, study design, outcome that was measured, the effect sizes, and sample sizes for each included study, academic domain, allocation, and face-to-face.
20	[53]	Online learning: Adoption, continuance, and learning outcome—A review of literature.	R. Panigrahi et al., (2019).	The application of technology to teaching and learning was considered. The usage of technology will lessen global issues like space, etc. This essay examines how combining online learning online learning	Collaborative learning, Team technology use, technology fit, context facilitation, social facilitation, and team cohesion.

				with a virtual community affects students' involvement and learning outcomes.	
21	[46]	Review on the Effect of Student Learning Outcome and Teaching Technology in Omani's Higher Education Institution's Academic Accreditation Process	Tawafak et al., (2018)	The component responsible for an institution's accreditation procedure is to determine how technology learning affects students learning.	Curriculum, teacher experience, learning outcomes of students, assessment method technology, and technology expansion.
22	[120]	Understanding Difficulties and Resulting Confusion in Learning: An Integrative Review	J. M. Lodge, G. Kennedy, L. Lockyer, A. Arguel, and M. Pachman (2018)	We aim to investigate difficulties in educational environments such as Because of larger class numbers and the usage of digital technology.	Incorporating emotional responses in learning.
23	[44]	Student	Gbollie et	Strategies aimed at	Utilization

		Academic Performance: The Role of Motivation, Strategies, and Perceived Factors Hindering Liberian Junior and Senior High School Students Learning.	al (2017).	investigating how to better the learning and motivation of students.	of learning strategies, learning barriers, and motivational beliefs
24	[49]	Interactivity in online discussions and learning outcomes	C. Kent et al., (2016).	The usage of online conversations in both official and informal learning contexts has expanded.	Explicit course content, content, social, and examples.
25	[55]	What works to improve the quality of student learning in developing countries?	S. Masino et al., (2016)	To increase education quality, three key factors are highlighted: supply, policy, and top-down or bottom-up participative.	Demand-side interventions, supply-side capabilities intervention, and incentives for altering

					preferences and behaviors.

3.3 Proposed Research Mechanism

Comparative analysis based on existing evaluation mechanism. Various academic emotions have been used in research papers to assess student learning outcomes. A comparative analysis of the various academic emotions in the evaluation mechanism is given below.

Table 3. 2 Comparative analysis based on evaluation mechanism

Sr. No.	Reference	Author and year	Learner's engagement /interest	Teaching context/ Experience	Learning Strategies/ Behavior	Technology Enhancement	Motivational Factors	Critical Thinking	Self Evaluation	Satisfaction/ Benefits
1	[124]	T. Adiguzel, M. H. Kaya, and F. K. Cansu (2023)	✓	✓	×	×	×	×	×	✓
2	[125]	X. Yu, N. Ma, L. Zheng, L. Wang, and K. Wang (2023)	✓	✓	×	×	×	×	×	✓
3	[126]	R. Ma and X. Chen (2022)	✓	×	×	×	×	×	✓	✓
4	[127]	M. A. Kuhail et al., (2022)	×	×	✓	×	×	×	×	×
5	[128]	S. J. H. Yang, H. Ogata, T. Matsui, and N.-S. Chen (2021)	×	×	✓	×	×	×	✓	✓

6	[129]	Z. Sun, M. Anbarasan, and D. Praveen Kumar (2020)	✓	✓	✓	×	×	×	×	×
7	[130]	A. Parmaxi et al.,(2020)	✓	×	×	✓	×	×	×	✓
8	[131]	Maxwell M. Yurkofsky (2019)	✓	✓	×	✓	×	×	✓	×
9	[132]	J. Hein et al.,(2019)	×	✓	✓	×	×	×	×	×
10	[60]	Stijn Van Laer et al.,(2019)	✓	×	✓	×	×	×	×	×
11	[48]	Alejandro Peña-Ayala et al.,(2019)	×	×	✓	×	×	✓	✓	×
12	[53]	Ritanjali Panigrahi et al.,(2018)	✓	×	✓	×	×	×	×	×
13	[133]	Simone E. Halliday et al.,(2018)	✓	×	✓	×	×	×	✓	×

3.4 Comparative analysis based on Technology

Technology plays a vital role in the student learning outcome. Various machine learning algorithms to evaluate Linear regression, Support vector machine (SVM), convolutional neural networks (CNN), etc. are used. Evaluation metrics are checked on the accuracy, error calculation specificity, etc.

Table 3. 2 Comparative analysis based on Technology

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
1	[134]	K. S. Selim and S. S. Rezk	2023	Egyptian survey dataset	Logistic Regression	Outperform	-	✓	-	-
2	[135]	R. M. Martins and C. Gresse Von Wangenheim	2023	Databases in the field of com-puting, including ACM Digital Library, IEEE Xplore, arXiv, Scopus, etc.	AI and ML Algorithm	-	-	✓	-	-
3	[136]	U. Ishfaq et al	2022	11 datasets derived from different domains	Naïve based, Decision Tree, Random	Ensemble-based GBDT's outperform. The	-	✓	-	-

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
				available in UCI and Kaggle repositories.	forest, CNN	recall of GBDTs on Spambase and Adult datasets is above 90%.				
4	[137]	M. Bari Antor et al	2021	The Open Access Series of Imaging Studies (OASIS) dataset has been used for the development of the system.	Support vector machine, logistic regression, decision tree, and random forest	92% (SVM)	-	✓	-	-
5	[138]	A. Kurani, P. Doshi	2020	The dataset consisted of 300 to 700 tuples ranging from 3 to 5 years which they got from the	SVM	60-70% (SVM)	-	✓	-	-

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
				website Quandl.						
6	[139]	A. Kowalska, R. Banasiak, J. Stańdo, M. Wróbel-Lachowska	2020	This dataset includes 1548 learning outcomes classified in three domains, gathered from 22 university databases/websites in a European Union country	Machine Learning	87%	-	✓	-	0.8
7	[140]	EU JIN PHUA 1, NOWSHATH KADHAR BATC	2020	4 datasets were generated with 1000 instances maximum for prediction and training too.	Linear Regression, Decision Table, and K-Nearest Neighbor. The Ensemble algorithms	74.8%	RMSE/AMSE (7.89)	✓	✓	-

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
		HA2			consist of Random Forest, Stacking, and Bagging.					
8	[141]	M. Barrón Estrada et al.,	2020	Sentences from movie reviews, and the Stanford Twitter Sentiment corpus (STS), which contains Twitter messages	Binary classification	85.70%	-	✓	-	-
9	[142]	A. A. Ardakani *et al.*	2020	100 wrists in 55 patients including 46 females and 9 males were used.	CNN	97.50%	-	✓	-	82% to 91.3%,
10	[143]	R. C. Ambagtshee	2020	Residential aged care administrati	SVM	Above 75%	-	✓	-	89.1

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
		r et al.,		ve data set.						
11	[144]	I. Hammad, K. El-Sankary, and J. Gu	2019	An open-source dataset that contains 24 ultrasound sensors	Decision Tree Classifier	Mean Accuracy 100%	-	✓	-	-
12	[145]	P. Sokkhey and T. Okazaki	2019	Two datasets namely, DS1, and DS2 of the same characteristics with different sizes were used	Multilayer Perceptrons, Support Vector Machine, Decision Tree, Logistic Regression, Random Forest.	93.52% (Random Forest)	-	-	✓	-
13	[146]	H. Wan et al.,	2019	The training dataset of TrAdaboost.	LR, support vector machine (SVM), and gradient	-	-	✓	-	-

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
					boosting decision tree (GBDT)					
14	[147]	D. Bogdanova and M. Snoeck	2019	17 example tables of learning outcomes related to content areas used	Classification	-	-	✓	-	-
15	[148]	A. M. Abubakar r et al.,	2019	152 valid responses from employees from the Aegean region.	ANN	Nearly 100%	MSE near to .000	✓	-	-
16	[149]	E. Yigit et al.,	2018	637 leaves consisting of 32 different plant species.	SVM	94.40%	-	✓	-	-

Sr.No	Ref.No.	Author	Year	Dataset utilized	Algorithm Utilized	Accuracy	Error calculated	Classification problem solved	Regression Problem solved.	Specificity
17	[150]	W. J. Lee et al.,	2018	Iron ironwork piece with the dimensions of 483 mm x 178 mm x 51 mm was used.	SVM	93%	-	✓	-	-

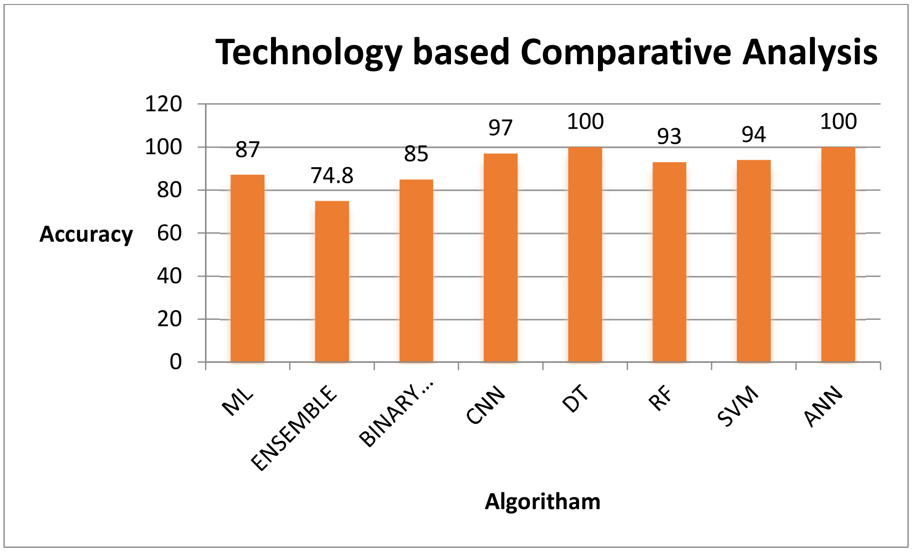

Figure 3. 1 Comparative analysis based on technology

Figure 3. 1 depicts the comparative analysis based on Table 3. 2. Various machine learning algorithms were applied to several datasets. The decision tree and artificial neural network give 100% accuracy in the above table. The X-axis shows the algorithm used and the y-axis shows the accuracy in percentage.

3.5 Comparative analysis of student's academic emotions

Academic emotions of the students measure the interest and understanding of the students during the class. Positive and negative emotions of the students are captured based on various parameters like enjoyment, confidence, enthusiasm, boredom, etc.

Table 3. 3 Comparative analysis based on student’s academic emotions

Sr. No	Ref No	Author and Year	Emotional Self-Awareness/ Engagement/ Interest	Stress Tolerance/Anxiety	Enjoyment	Confidence/Pride	Enthusiasm/ Passion/ Hope	Boredom	Anger/ Frustration/ Irritation	Examination score	Teaching effectiveness	Students' Mental health	Framework Capability
1	[151]	J. X.-Y. Lek and J. Teo(2023)	✓	✓	✓	×	×	×	✓	×	×	×	×
2	[152]	M. Ravichandran and G. Kulanthaivel (2023)	×	×	×	×	×	×	×	✓	✓	×	×
3	[153]	X. Xie and J. Guo(2022)	✓	✓	✓	✓	✓	✓	✓	×	×	✓	×
4	[154]	J. Zheng, S. P. Lajoie, S. Li, and H. Wu (2022)	✓	✓	×	✓	✓	✓	✓	×	×	×	×
5	[155]	S. M. St Omer, O. A. Akungu, and S. Chen(2022)	×	✓	×	✓	✓	✓	✓	×	×	×	×
6	[156]	J. Zawodniak, M. Kruk, and M. Pawlak (2021)	×	✓	×	×	×	✓	✓	×	×	×	×
7	[157]	P. C. Parker *et al.*, (2021)	×	✓	✓	×	×	✓	×	×	×	✓	×

Sr. No	Ref No	Author and Year	Emotional Self-Awareness/ Engagement/ Interest	Stress Tolerance/Anxiety	Enjoyment	Confidence/Pride	Enthusiasm/ Passion/ Hope	Boredom	Anger/ Frustration/ Irritation	Examination score	Teaching effectiveness	Students' Mental health	Framework Capability
8	[158]	S. Rahimi and R. J. Vallerand (2021)	×	✓	×	×	✓	×	✓	×	✓	✓	×
9	[159]	M. Sadoughi and S. Y. Hejazi(2021)	×	×	✓	✓	✓	×	×	×	✓	✓	×
10	[160]	H. Wang, A. Peng, and M. M. Patterson (2021)	×	✓	✓	✓	×	✓	×	×	✓	✓	×
11	[161]	C. Skaalvik (2020)	✓	✓	✓	×	×	×	×	×	×	✓	×
12	[162]	K. Jeongyeon and S. Hye Young (2020)	×	×	✓	✓	×	×	×	×	×	✓	×
13	[163]	A. Westphal, J. Kretschmann, A. Gronostaj, and M. Vock (2018)	×	×	✓	×	×	✓	×	×	×	✓	×

3.6 Results and Discussions

In this chapter examination and evaluation systems available in existing research papers have been reviewed. Assessment has been done on a quantitative basis where the marks of the students are considered as the primary factor. During the literature survey, both qualitative and quantitative aspects of the student's assessment have been considered. The contribution of artificial intelligence and machine learning has been studied and considered. Comparative analysis based on an evaluation mechanism has been done which includes the quality of teaching, student engagement, self-evaluation, etc. In the comparative analysis based on technology various algorithms of machine learning along with its accuracy, errors, etc. have been considered. The divisions of algorithms are done based on regression and classification problems. Most importantly academic emotions need to be incorporated for better assessment of learning outcomes. The academic emotions of the students found in the literature survey compared with the academic emotions are used in the proposed research work.

CHAPTER 4

DESIGN A REAL TIME MECHANISM FOR CAPTURING A STUDENT LEARNING AND THEIR ACADEMIC EMOTION

4.1 Introduction

The World Wide Web provides many platforms to express user's opinions and emotions about a particular event, product, place, brand, etc., and applications like social networks, discussion forums, and blogs have a great influence on organizations and customers. Similarly, feedback is extremely important in education as it represents the student's emotions about learning which helps in the modification and improvement of student learning outcomes [4]. To gauge the emotional state of students concerning teachers, homework, and academic project parameters like engaged, excited, and disengagement are evaluated using the sentimental analysis. Many methodologies in emotional analysis, such as EvoMSA, have been used to compare different classifiers utilizing machine learning, deep learning, and evolutionary approaches. The framework (EvoMSA) has been tested for many domains such as humor analysis for providing positive or negative emotions [140]. One more system, the FaceReader system recognizes different emotions such as pleasure, grief, anxiety, irritation, surprise, and neutrality by using a neural network for generating and determining training, test samples, and a rational number of neural network layers [164].

The academic development of the student is influenced by the student's achievement and emotions like enjoyment, anxiety, and boredom. Moreover, teachers need to create good diagnostic tools and methods to improve a positive emotional learning environment and less anxiety and boredom [162]. Emotions like enjoyment and relaxation show the relationship between teacher support and creative self-efficacy [165]. Achievement emotions related to education such as sports, motivation, self-regulatory, and cognitive processes have a direct connection with them, as they play an important role in providing academic escalation throughout the semester [166].

Similarly, the Socrative tool is also used for real-time assessment of students' cross-sectional competencies via the Internet to answer the questionnaire. After submission of the questionnaire, results are displayed to both students and teachers, thus increasing the interest, skills, and abilities of the students [167]. Because of its potential influence on all levels of education, real-time evaluation of student performance is a key issue in learning analytics research.

It provides unbiased data when different feedback is captured in the system. In the present work, feedback is captured and accessed by a novel framework TERE (Teaching Effectiveness Rating Engine) to measure the academic emotions of students in an institution. The proposed research work deals with the TERE framework to capture real-time feedback on a Likert scale of five. The dataset generated in TERE is a granted Indian copyright (copyright number SW-14125/2021), which has five parameters with 11000 records of 590 courses. To measure these emotions about a particular lecture, specify the Quality of content, Examples & Application, Doubt clearing & interaction, Quality of delivery, and Value Addition. The TERE data is stored using positive and negative emotions varying from unhappy to happy. In the proposed work real-time assessment of students' emotions has been assessed. As soon as students attend the lecture, they will feed their academic emotions about it. This will provide a true measure and an unbiased emotion about the lecture's content, delivery, examples, interaction, value additions, etc. Five parameters to measure the academic emotions of the students rated from 5 to 1 (i.e., happy = 5 to unhappy = 1) and are captured on a smiley bar. These parameters are named as quality of content, Examples and application, Doubt clearing & Interaction, Quality of Delivery, and Value addition.

Further, the use of machine learning algorithms in recommendation systems provides users with item recommendations and new research opportunities [168]. The Recommender System delivers a real-time assessment of a student's learning efficiency, curiosity in learning, and course selection [117]. Learning outcomes can be affected by many parameters and to see whether a student has perceived the course content properly corresponding to learning outcomes or not [169]. In recent years, the research interest in emotion recognition is increasing therefore it is crucial to identify the academic emotions of the students. During the class, five parameters i.e., quality of content, Examples/ Application, Doubt clearing & Interaction, Quality of Delivery, and Value addition play an important role in student engagement and immersive learning of the student. Quality of content plays a significant role as the content of the lecture is the base through which students are going to learn the desired content.

Examples and applications make the content understandable in-depth and explain the intent of the lecture by correlating concepts with real-life happenings. Doubts of the students are cleared or solved to enhance interaction with a student. Quality of delivery should be simpler and understandable and value addition is also an important parameter for improving student's foresightedness. The educational emotional state of education can be modified with educational content [170]. Students can play an important role in the improvement of the teaching-learning process by giving candid feedback. Feedback is an important source of information for teachers as well [171]. To capture the feedback of the students on the aforementioned parameters immediately after the class a system is designed, developed, and deployed.

4.2 Process of course outcome attainment

Nowadays, students' assessment grades are used to assess their learning outcomes. The intent of current research is on how learning outcomes are alleged and applied at various points for assessing students' grades [172]. Curriculum alignment, or assessing the educational program's defined learning outcomes, is a best assessment practice. Course outcomes attainment is the measure of quantity-oriented learning outcomes which represents quantitative data about students learning [173]. Different assessment formats depend on the genre and academic discipline [174]. Engineering education is highly structured and driven by knowledge attributes, course outcomes, and program outcomes with a focus on student self-learning. Pedagogical strategies for achieving course outcomes vary by course, active learning techniques, and assessment achievement is calculated by a student's response to their performance [175]. Advancing the assessment of undergraduate and graduate student learning outcomes is essential for the advancement of higher education [176]. In the proposed work, the quantitative model consists of COs which are a measure of learning outcome based on the performance of the student in the class assignment, mid-term, and end-term evaluation. Questions given in-class assignments, mid-term, and end-term are mapped with COs. The questions designed will be associated with appropriate COs and the performance of students for a particular question would be a measure to understand how much learning outcome has been attained with the associated CO. CO is attained using a three-level threshold: 1 - low, 2 - medium, and 3 - high. Levels 3, 2, and 1 range from 70% and above, 60% -69%, and 51-59% of students score more than the set threshold marks. Level 0 is less than and equal to 50% of students scoring more than the set target marks.

4.2.1 Creating CO master for C513 – Course title

Table 4. 1 Course CO Master

Course Code	CO#	Description
CSE513	CO1	Real-world examples are used to learn to program.
CSE513	CO2	To learn how to use the C++ programming language to find solutions to various problems using an object-oriented approach.
CSE513	CO3	Providing solutions to a variety of everyday problems Using C++.
CSE513	CO4	To become familiar with the object-oriented approach.
CSE513	CO5	Evaluate the working of projects based on the object-oriented approach.

In table 4. 1 Course, CO Master includes course codes and COs with their description.

4.2.2 Course CO mapping lecture wise

Table 4. 2 Course CO Mapping

Lecture No.	Course Code	CO	Description
L1	CSE513	CO2	Introduction to OOPS
L2	CSE513	CO2	Basic OOP features
L3	CSE513	CO1	Components of a C++
L4	CSE513	CO1	Program and its structure
L5	CSE513	CO1	Compilation and Execution of C++ Program
L6	CSE513	CO1	Differentiate Procedure-Oriented Language(C) and Object-Oriented Language (OOL)
L7	CSE513	CO2	Concept of Constructors with classes

Lecture No.	Course Code	CO	Description
			and objects
L8	CSE513	CO4	Defining classes
L9	CSE513	CO4	Defining member functions
L10	CSE513	CO4	Object declaration to a class

In table 4. 2 course CO mapping has been done. In this table, lecture-wise mapping with CO has been done. From this mapping, crisp identification of the number of lectures corresponding to a CO like in lectures L3, L4, L5, and L6 topics covered pertain to CO1. This is a micro-level mapping of CO with the lecture. The level mapping can be summed up to get macro-level mapping e.g. unit-wise and course-wise learning outcomes can be attained.

4.2.3 CO mapping with CA's, MTT and ETT

Table 4. 3 CO Mapping with CA's, MTT, and ETT

Course Code	CO	CA1	CA2	MTT	ETT
CSE513	CO1	Y		Y	Y
CSE513	CO2	Y	Y		Y
CSE513	CO3	Y	Y	Y	Y
CSE513	CO4		Y	Y	Y
CSE513	CO5				Y

Table 4. 3 shows the CO mapping with CA's, MTT, and ETT. CA1 included questions mapped with CO1, CO2, and CO3. MTT included questions mapped with CO1, CO3, and CO4. ETT included questions mapped with CO1, CO2, CO3, CO4, and CO5.

4.2.4 CO Level

Table 4. 4 CO level

		CA1(30 Marks)			CA2(30 Marks)			MTT (40 Marks)			ETT (70 Marks)				
		CO1	CO2	CO3	CO2	CO3	CO4	CO1	CO3	CO4	CO1	CO2	CO3	CO4	CO5
Subject Code	Max Marks	10	10	10	10	10	10	10	15	15	5	10	15	20	20
CSE 513	Cut off Marks (40%)	4	4	4	4	4	4	4	6	6	2	4	6	8	8
CSE 513	Students Above 40% Cut off	310	392	338	350	398	385	360	400	382	355	312	410	400	321
CSE 513	Max Student	550	550	550	540	540	540	525	525	525	540	540	540	540	540
CSE 513	% above cutoff Marks	56	71	61	65	74	71	69	76	73	66	58	76	74	59
CSE 513	CO Value	1	3	2	2	3	3	2	3	3	2	1	3	3	3

Table 4. 7 shows a detailed matrix to find the CO level. CO is attained based on the threshold in three levels: 1 is Low; 2 is medium, and 3 is High. In this table, CA1, CA2, MTT, and ETT have been defined. In Table 4. 3 CO Mapping with CA's, MTT, and ETT has been done and CA1 included questions aligned to CO1, CO2, and CO3 and so on with CA2, MTT, and ETT. Max Marks show maximum marks corresponding to the COs Cut-off marks are 40%. "Percentage above cut-off marks" shows % of students who have scored above cut-off marks and CO values have been assigned accordingly.

4.2.5 Calculation of CO weightage

Table 4. 5 Calculation of CO Weightage

		CA 1	CA2	MTT	ETT	Attainment
Subject	Weightage	10	15	20	50	
CSE513	CO1	1		2	2	1.88
CSE513	CO2	3	2		1	1.47
CSE513	CO3	2	3	3	3	2.89
CSE513	CO4		3	3	3	3.00
CSE513	CO5				3	3.00

Table 4. 5 depicts the weights of CA's, MTT, and ETT corresponding to CO. In this CA's has a weightage of 25%, MTT has a weightage of 20% and ETT weightage is 50%. CO attainment for CO1 is calculated using the formula. 5% is allocated to attendance which is not considered to be participating in attainment.

$$CO1 = \quad Weightage * CO1 + weightage * MTT + Weightage * \mathrm{ETT} / (Weightage\ of\ CO1 + Weightage\ of\ MTT + Weightage\ of\ ETT) \tag{1}$$

$$CO1 = 10 * 1 + 20 * 2 + 50 * \frac{2}{80} = 1.87\ and\ likewise.$$

4.2.6 CO attainment

Table 4. 6 CO attainment

COURSE CODE	CO	ATTAINMENT
CSE513	CO1	1.88
CSE513	CO2	1.47
CSE513	CO3	2.89
CSE513	CO4	3.00
CSE513	CO5	3.00

Table 4. 6 depicts overall CO attainments. The same steps are followed to calculate the CO attainment for any course code.

4.3 Comparative analysis based on the Quantitative measures

Table 4. 7 Comparative analysis of the qualitative measures with existing and proposed parameters.

Sr. No.	Ref. no.	Author and Year	Score Achieved /Grades	Learning Outcome	Quiz/test	Discussion	Questionnaire	Effects of assessment on learning	Fairness of assessment	Conditions of assessment	Authenticity of assessment	Oral presentation	Written reports	Interview	Proposed Parameters
															CO attainment based on ETT Marks, MTT, marks and assignments.
1	[177]	P. Tschisgale, P. Wulff, and M. Kubsch (2023)	✓	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✓	✗
2	[178]	C. Cecilia (2023)	✗	✓	✗	✗	✓	✓	✓	✗	✓		✓		✗
3	[179]	E. Widnall et al (2022)	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗

Sr. No.	Ref. no.	Author and Year	Score Achieved /Grades	Learning Outcome	Quiz/test	Discussion	Questionnaire	Effects of assessment on learning	Fairness of assessment	Conditions of assessment	Authenticity of assessment	Oral presentation	Written reports	Interview	Proposed Parameters CO attainment based on ETT Marks, MTT, marks and assignments.
4	[180]	J. Nogueira, B. Gerardo, I. Santana, M. R. Simões, and S. Freitas (2022)	✓	×	✓	×	✓	✓	✓	✓	×	×	×	×	×
5	[181]	R. Saltos-Rivas, P. Novoa-Hernández, and R. Serrano Rodríguez (2021)	×	×	×	×	✓	✓	✓	×	×	×	×	×	×
6	[182]	J. M. Nissen, I. Her Many Horses, and B. Van Dusen(2021)	✓	✓	✓	×	×	×	×	×	×	×	×	×	×
7	[183]	S. Chatterjee, K. K. Bhattacharjee, C.-W. Tsai, and A. K. Agrawal (2021)	×	×	×	×	✓	×	×	×	×	×	×	×	×

Sr. No.	Ref. no.	Author and Year	Score Achieved /Grades	Learning Outcome	Quiz/test	Discussion	Questionnaire	Effects of assessment on learning	Fairness of assessment	Conditions of assessment	Authenticity of assessment	Oral presentation	Written reports	Interview	Proposed Parameters CO attainment based on ETT Marks, MTT, marks and assignments.
8	[184]	A. Purwanto (2021)	×	×	✓		✓	×	×	×	×	×	×	×	×
9	[185]	K. M. Hammond and S. Brown (2021)	✓	✓	×	×	×	×	×	×	×	×	×	×	✓
10	[186]	A. Gegenfurtner, A. Zitt, and C. Ebner (2020)	✓	✓	×	✓	✓	×	×	✓	×	×	×	✓	×
11	[187]	D. Hamilton, J. McKechnie, E. Edgerton, and C. Wilson (2020)	✓	✓	✓	✓	✓	×	×	✓	×	×	✓	✓	×

Sr. No.	Ref. no.	Author and Year	Score Achieved /Grades	Learning Outcome	Quiz/test	Discussion	Questionnaire	Effects of assessment on learning	Fairness of assessment	Conditions of assessment	Authenticity of assessment	Oral presentation	Written reports	Interview	Proposed Parameters: CO attainment based on ETT Marks, MTT, marks and assignments.
12	[188]	D. Popa, A. Repanovici, D. Lupu, M. Norel, and C. Coman (2020)	×	×	×	×	×	✓	✓	×	×	×	×	✓	×
13	[189]	M. Y. Ahn and H. H. Davis (2020)	×	×	×	×	✓	×	×	×	×	×	×	×	×
14	[175]	K. C. Chilukuri (2020)	×	✓	✓	✓	×	×	×	×	×	×	×	×	✓
15	[47]	K. J. Gerritsen-van Leeuwenkamp, D. Joosten-ten Brinke, and L. Kester (2019)	✓	✓	✓	×	✓	✓	✓	✓	✓	×	×	×	✓

Sr. No.	Ref. no.	Author and Year	Score Achieved /Grades	Learning Outcome	Quiz/test	Discussion	Questionnaire	Effects of assessment on learning	Fairness of assessment	Conditions of assessment	Authenticity of assessment	Oral presentation	Written reports	Interview	Proposed Parameters: CO attainment based on ETT Marks, MTT, marks and assignments.
16	[190]	M. Tobajas, C. B. Molina, A. Quintanilla, N. Alonso-Morales, and J. A. Casas (2019)	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓

4.4 Proposed Design of TERE framework for capturing a student's learning and their academic emotions

TERE framework is used to capture and collect real-time data after each lecture. The teaching effectiveness rating engine (TERE) is a real-time review of what is happening in the classroom and it will bridge the gap between lecture delivery and assessment. For lectures, students follow a timetable that includes the room number, time of the class, course code, faculty, etc. On the other side, teachers have an Instruction plan (IP) Master. IP master includes course-wise, lecture-wise content, and pedagogical tools of the course. Using TERE an aggregation of lecture content, pedagogical tools, examples, etc. mapped with the student's lecture. The aggregator in the TERE framework performs the mapping process of timetable content to be delivered in the lecture and the presence of students to capture real-time feedback on a particular lecture. Five Likert scales are used to measure the student's emotions (1-unhappy, 2 -somewhat unhappy, 3- neutral,4- somewhat happy, 5 happy). The overall emotions of the students can be calculated by using an overall average of the above parameters. If the learning outcome of the lecture is not achieved then the TERE dataset can be used to see the correlation between five parameters and overall CO attainment. TERE framework will help to give a clear picture of academic emotions as it gives real-time feedback about a lecture. Good ratings given by the students to parameters show satisfaction with their emotions. However, the learning process is generally accompanied by emotional experiences, which can have an impact on students' involvement in the course, eventually leading to underperformance and dropout [191]. Figure 4.1 shows the interface of the TERE framework.

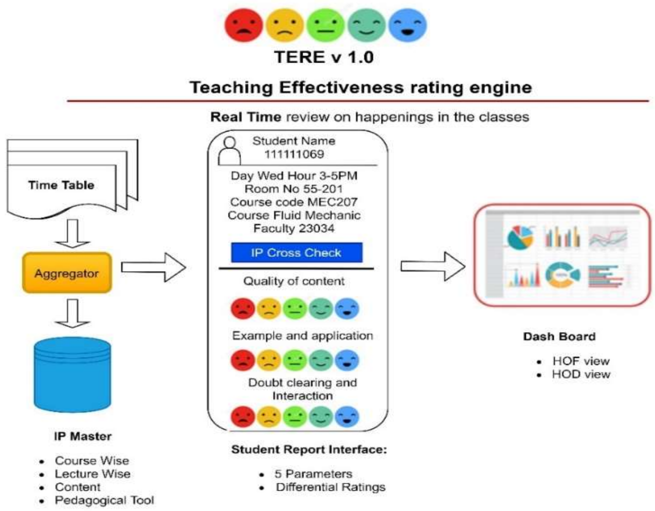

Figure 4. 1Teaching Effectiveness Rating Engine (TERE)

Figure 4. 1 depicts the teaching effectiveness rating engine. It has time table, Instruction plan (IP) master, Student report interface, and dashboard. In this figure first view of the TERE framework is depicted.

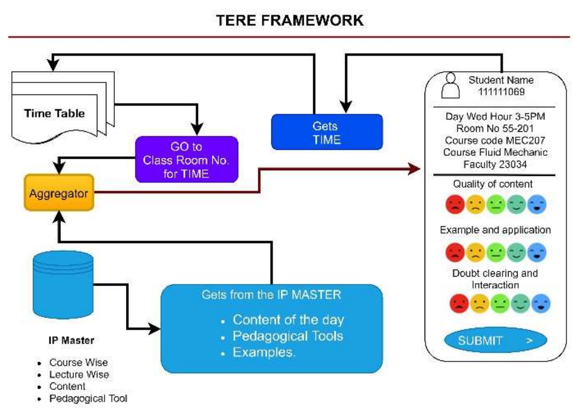

Figure 4. 2 TERE need and necessity

Figure 4. 2 shows the TERE framework's need and necessity. Students use mobile applications to check the timetable & classroom as per time. Aggregator connects to the IP master to get the content and pedagogy of the lecture.

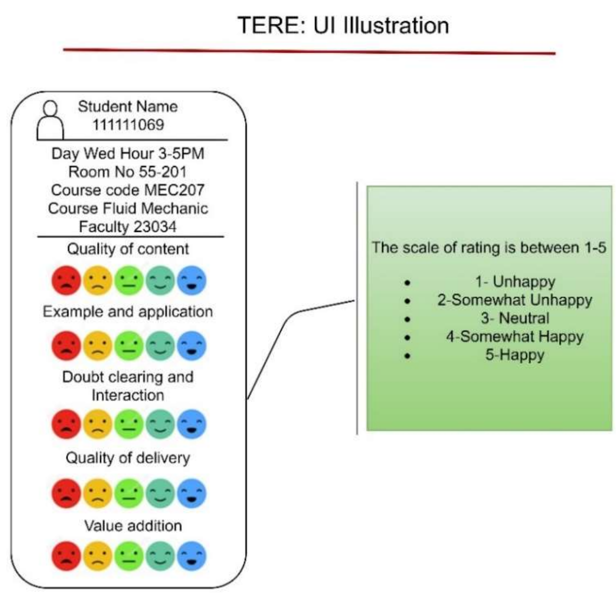

Figure 4. 3 TERE user interface

Figure 4. 3 is the subsection of Figure 4.2, which shows the five academic emotions of the TERE user interface in a smiley form. TERE academic emotions of the students are captured on below mentioned 5 Lickert scale as follows:

1 – Unhappy

2 – Somewhat Unhappy

3 – Neutral

4 – Somewhat happy

5 – Happy

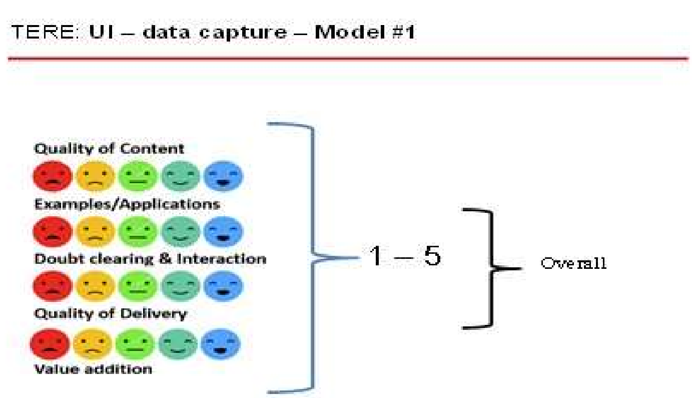

Figure 4. 4 Overall Academic Emotions

Figure 4. 4 shows the overall academic emotions of the students in the TERE framework.

4.5 Rules for capturing Academic Emotions in TERE Framework

- The interface is available on LPU TOUCH – The mobile app available to students.
- Students who had attended the class and marked 'Present' can only give feedback.
- The reporting can be done within 48 hours of the conduct of the class.
- Less than 5 feedback on a particular course should be considered as an outlier.
- To overcome less than 5 feedback points, Feedback should be compulsory for all students.
- If the total attendance percentage is less than 25% then feedback from that student should not be considered.
- High weightage can be given to the student's feedback with a higher attendance percentage.
- If a student dropped out of the course at any point throughout the semester, the data were removed from the analysis.
- Feedback might be given numerically or nominally.
- If a student gives multiple feedback to a teacher only, it will be considered.

4.6 Feedback process followed by students

Step 1 Students log in to the LPU Touch interface.

Step 2 Select the course.

Step 3 Select the lecture number.

Step 4 Student gives feedback on the quality of content, examples, and applications, doubt clearing and interaction, quality of delivery, and value addition of these parameters.

Step 5 Students submit the feedback.

4.7 Comparative analysis based on the Qualitative measures

Table 4. 8 Comparative analysis of the qualitative measures with existing and proposed parameters

Sr. No	Author and Year	Ref. No	Self-Regard Determination	Emotional Self-awareness/ engagement	Enjoyment	Hope	Enthusiasm/ Passion	Pride	Anxiety	Boredom	Interest	Irritation	Nervousness	Learning	Learners Profile	Proposed Parameters				
																Quality of content	Example and applications	Doubt clearing and Interaction	Quality of delivery	Value addition
1	G. Margarita, Nelly Ramírez Vazquez, and C. Alicia (2023)	[192]	✓	×	✓	×	✓	×	✓		✓	×	×	✓	×	✓	×	×	×	×
2	A. Ritoša et al (2023)	[193]	×	✓	×	×	×	×	×	×	✓	×	×	✓	×	×	×	✓	×	✓
3	Q. Xu, S. Chen, Y. Xu, and C. Ma (2023)	[194]	×	×	✓	✓	✓	✓	✓	✓	✓	×	×	×	×	✓	×	✓	×	×
4	D. Zhang, S. Gao, and R. Liu (2023)	[195]	×	✓	✓	✓	×	✓	✓	×	×	✓	×	✓	×	✓	×	✓	×	×
5	] Z. Atiq and M. C. Loui (2022)	[196]	×	×	×	✓	×	✓	✓	✓	×	✓	×	×	×	×	×	✓	×	✓
6	M. Hooda, C. Rana, O. Dahiya, A. Rizwan, and M. S. Hossain (2022)	[113]	✓	✓	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×

7	J. Zheng, L. Huang, S. Li, S. P. Lajoie, Y. Chen, and C. E. Hmelo-Silver (2021)	[115]	✗	✗	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
8	A. Abbas, S. Hosseini, J. Escamilla, and L. Pego (2021)	[197]	✗	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
9	A. Gegenfurtner, A. Zitt, and C. Ebner (2020)	[186]	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗		✓	✓	✗	✗	✓	✗	✗
10	J. Lönngren et al (2020)	[198]		✓	✓		✗	✗	✓		✓	✗	✗	✓		✗	✓	✓	✗	✗
11	A. Parmaxi (2020)	[130]	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✗	✗	✗
12	X. Feng, Y. Wei, X. Pan, L. Qiu, and Y. Ma (2020)	[199]	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
13	S. P. Lajoie, R. Pekrun, R. Azevedo, and J. P. Leighton (2019)	[106]	✗	✗	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗
14	J. A. R. Eliot and A. Hirumi (2019)	[200]	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗

4.8 Tabular representation of the TERE features and data values

Feature selection is a very important part of a machine learning model to increase the performance of the model. By using feature selection number of input variables is reduced. It reduces the computational cost of the model. All the features of TERE dataset are depicted in Table 4.9, but features like session, registration_No, Course_code, Lecture_Date, Lecture_Time, Lecture_no, Teacher_Id, Course_Section, Course_TermID, and Response_dateTIme are not been used for data analysis. These features explain the basic details of the particular lecture.

Table 4. 9 Variables of TERE dataset for data analysis

Variables	Attributes
Session	INT64
Registration No	INT64
Course code	OBJECT
Lecture_Date	DATETIME64
Lecture_Time	OBJECT
Lecture_no	INT64
TeacherID	INT64
Course_Section	OBJECT
Course_TermId	INT64
Response_dateTime	Date
Quality_Of_Content	INT64
Example /Applications	INT64
Doubt clearing and interaction	INT64
Quality of delivery	INT64
Value addition	INT64
MTTMarksMax	INT64
MTTMarksObtained	INT64
ETTMarksMax	INT64
ETTMarksObtained	INT64

Only five features quality of content, Examples/ Applications, Doubt clearing and interaction, Quality of Delivery, and Value addition used or the data analysis and academic emotion have been calculated based on these parameters. In the TERE dataset, participating features were identified and the rest were dropped.

Table 4. 10 Overview of TERE Framework Parameters

Quality of content	Examples/ Application	Doubt clearing & Interaction	Quality of Delivery	Value addition	MTT Marks Max	MTT Marks Obtd	ETT marks Max	ETT Marks Obtd
4	4	4	4	4	40	23	100	65
4	3	1	1	3	40	25	100	65
5	5	3	4	4	40	13	100	58
4	4	3	3	3	40	37	100	79
5	5	4	5	5	40	2	100	12
2	3	2	1	1	40	18	100	77
4	4	4	4	4	40	6	100	52
4	5	4	4	5	40	4	100	72
5	4	5	5	4	40	11	100	52

In Table 4. 10, different ratings on the five-point Likert scale for the respective features have been given by the students on a real-time basis.

4.9 Result

The result section is divided into various sub-sections which include course-wise measurement of academic emotions, course-wise average rating of marks, marks and average academic emotions of the students, and course average rating of individual students to find their minimum, maximum, and average rating.

4.9.1 Plotting of overall academic emotions and marks

Here, overall academic emotions and percentage of marks were considered to see the overall correlation between the MTT Marks and academic emotions. Academic emotions were considered one by one corresponding to the percentage of marks. The percentage of marks considered as a maximum mark varies from course to course. Further, the following charts show the average rating by the students on the Y-axis and the percentage marks obtained by them on the X-axis. Here the percentage of marks is taken because the maximum marks for the mid-term examination vary in different course codes.

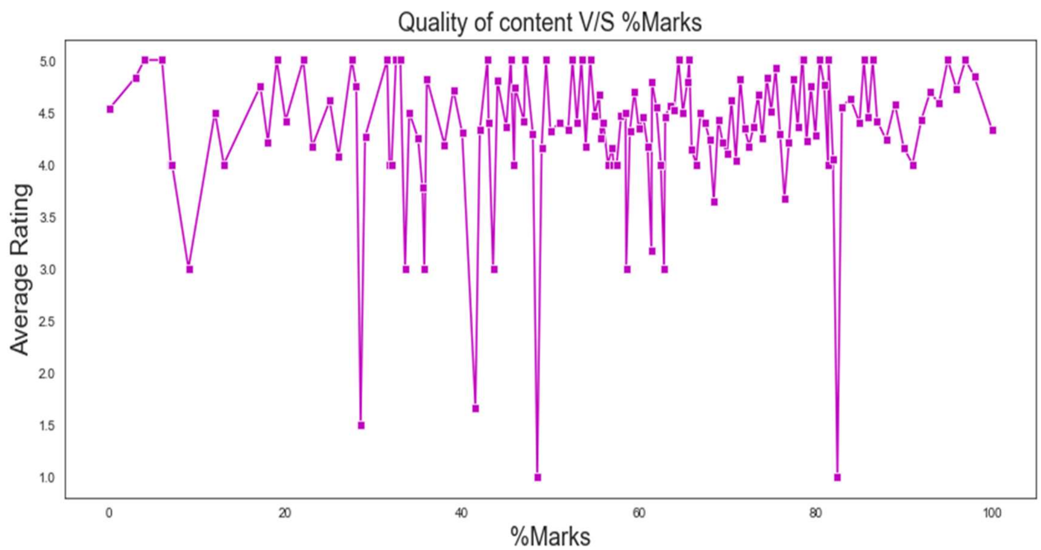

Figure 4. 5 Average rating of the quality of content with a percentage of marks

Fig. 4. 5 shows % of marks obtained on the x-axis and the average rating on the y-axis. Figure 4.5 shows that when marks obtained were 0% the average rating of the students was 4.53, at 9% marks average rating of the quality of the content was 3 and at 94% marks, the average rating of the quality of the content was 4.58.

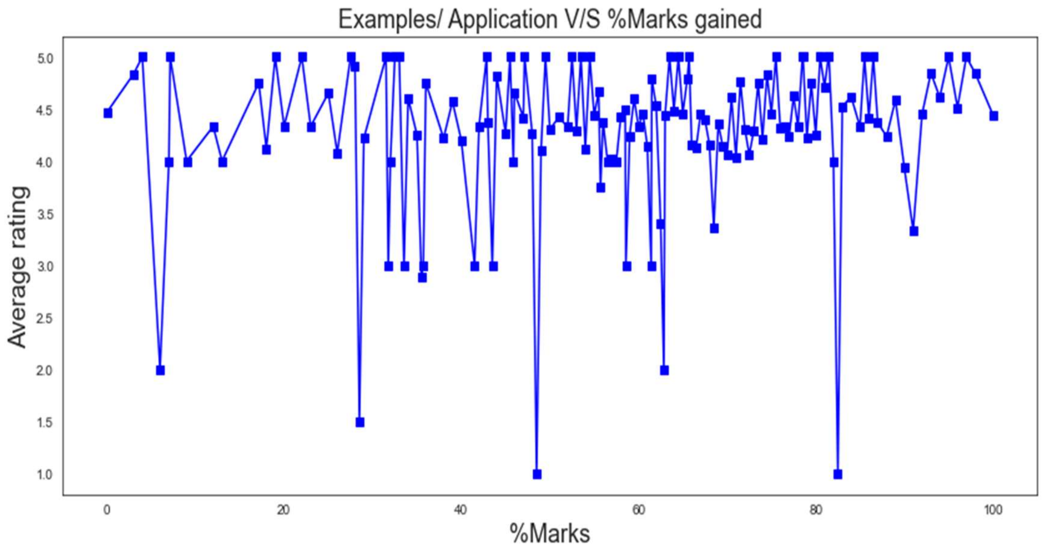

Figure 4. 6 Average rating of example/application with a percentage of marks

Fig.4. 6, the x-axis represents marks achieved in MTT and the average rating on the y-axis. Here 0% marks were obtained having students' average rating of 4.47, at 19% marks average rating of example and application was 5, and at 94% marks average rating of example and application was

4.61.

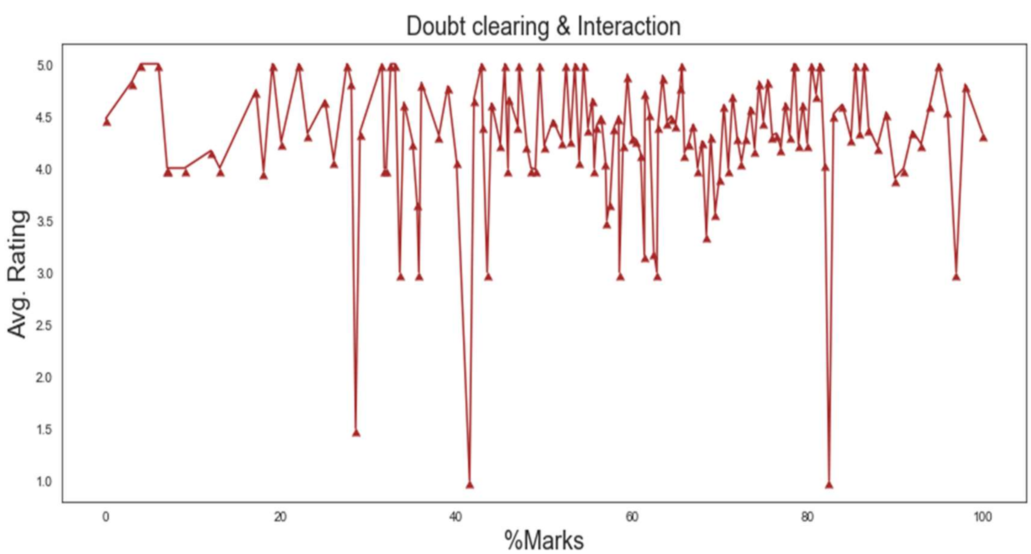

Figure 4. 7 Average rating of doubt clearing and interaction with a percentage of marks

Figure 4. 7 shows % of marks obtained on the x-axis and the y-axis represents the ratings. When the percentage of marks was 4 average rating of the students was 5, at 49% marks average rating of doubt clearing and interaction was 3.9, and at 91% marks, the average rating of the quality of the content was 4.

Figure 4. 8 Average rating of Quality of Delivery with a percentage of marks

Figure 4. 8 shows % of marks obtained on the x-axis and average rating on the y-axis. When the percentage of marks was 4% average rating of the students was 5, at 43% marks average rating of the quality of delivery was 4 and at 85% marks, the average rating of the quality of delivery was 5.

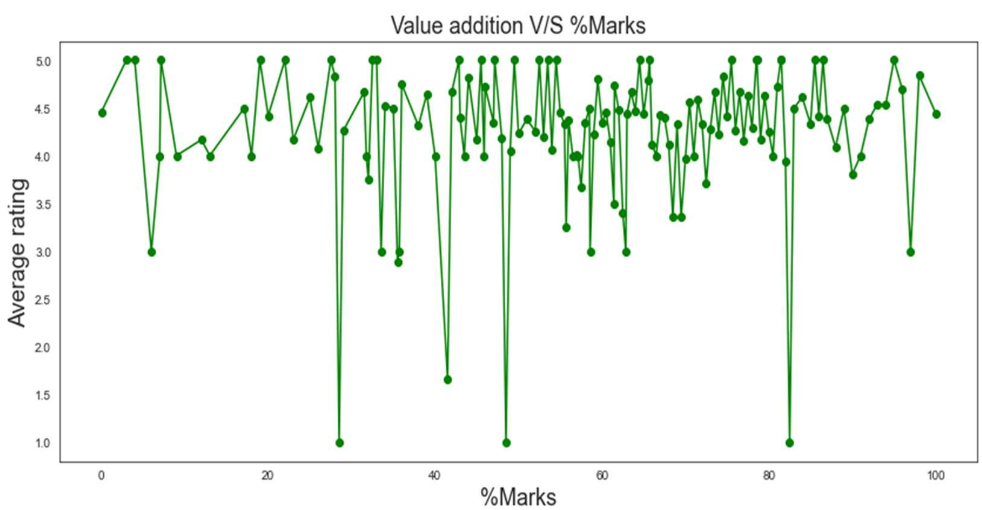

Figure 4. 9 Average rating of value addition with the percentage of marks

Figure 4. 9 shows % of marks obtained on the x-axis and average rating on the y-axis. When the percentage of marks was 5% average rating of the students was 3, at 40% marks average rating of value addition was 4, and at 95% marks, the average rating of the quality of the content was 5.

4.9.2 Course-wise average rating with marks

To achieve a course-wise learning outcome suitable learning environment and recourses need to be provided to the learners [201]. Alignment of an assessment process and learning outcomes is necessary to achieve outcomes-based assessment [202]. In the TERE dataset out of these 592 courses, three-course codes have been selected to see the rating of five parameters with marks in these particular courses. This will help to see the overall academic emotions of these courses. Three courses have been taken to see the correlation between MTT Marks obtained with academic emotions. Figures 4-10, 4-11, 4-12, 4-13, and 4-14 graphically represent the course-wise rating of individual academic emotion and MTTMarks.

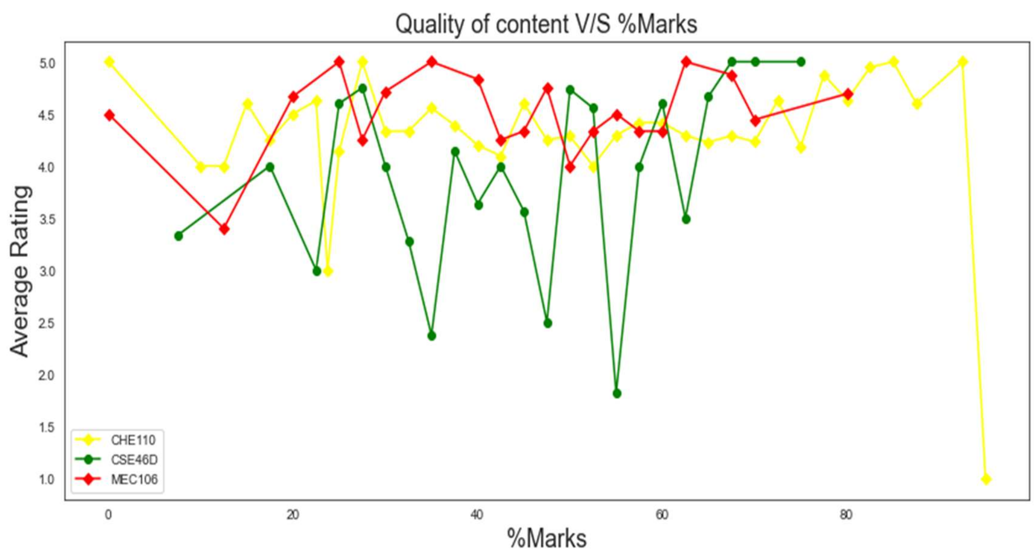

Figure 4. 10 Quality of content and MTTMarks in selected three course codes

Figure 4.10 shows the first parameter of academic emotions i.e. quality of content with a percentage of marks in a three-course. The x-axis shows the percentage of marks in mid-term and the y-axis shows ratings from 1-5. For example, students who scored 0% percent marks had an average rating of 5 in course code CHE110 and 4.5 in course code MEC106 in quality of content. This shows that even the students with 0% marks were happy with the quality of the content. In other cases, students with 40% marks had a 4.2 rating in CHE110, 3.6 rating in CSE46D, and MEC106 had a rating of 4.8.

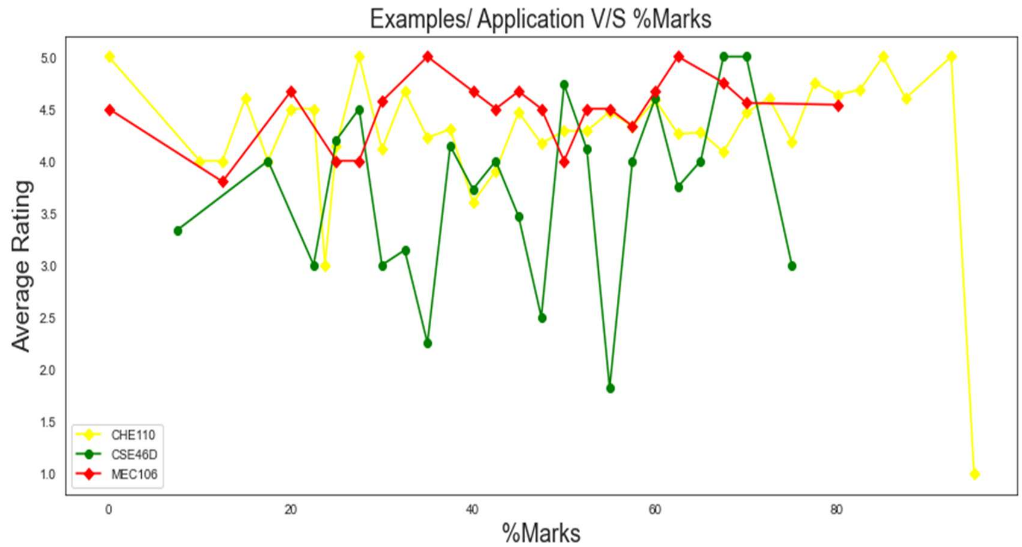

Figure 4. 11 Examples/Applications and MTTMarks in a selected three course code

Figure 4. 11 shows examples and applications of three courses i.e. CHE110, CSE46D, and MEC106. In the above graph, the x-axis shows the percentage of marks and the y-axis shows ratings from 1 to 5, and students scoring 25% marks have an average rating of 4.1, 4.2, 4.0 in respective course codes CHE110, CSE46D, and MEC106 and students with 40% marks had a rating of 3.6, 3.7, 4.6 in example and application in course codes CHE110, CSE46D, and MEC106.

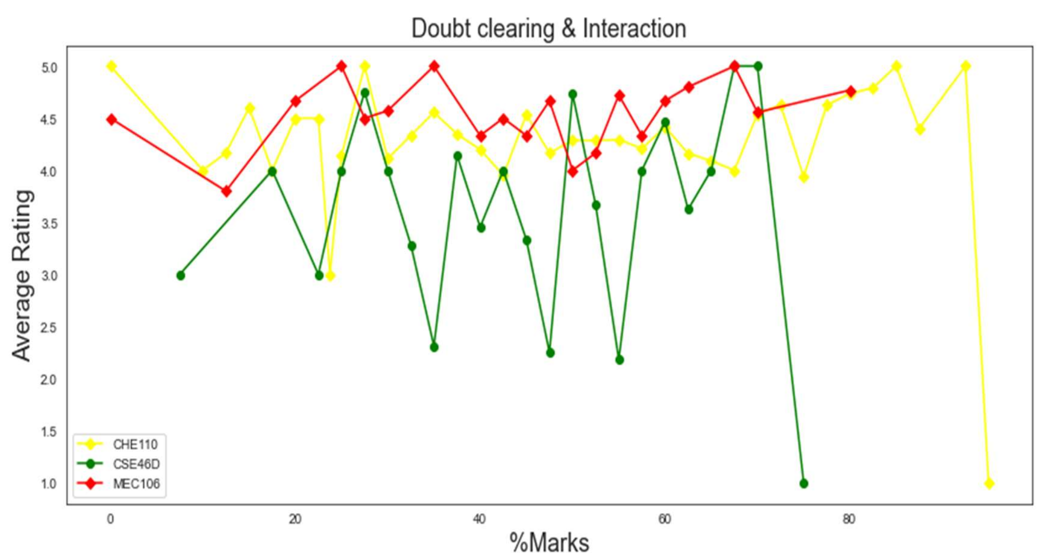

Figure 4. 12 Doubt clearing and interaction and MTTMarks in a selected three course code

Figure 4. 12 shows doubt clearing & interaction of three courses i.e. CHE110, CSE46D, and MEC106. In the above graph, the x-axis shows the percentage of marks and the y-axis shows ratings from 1 to 5, and students scoring 30% marks have an

average rating of 4.1, 4.0, 4.5 in respective course codes CHE110, CSE46D, and MEC106 and students with 40% marks had a rating of 4.2, 3.4, 4.3 in doubt clearing and interaction in course codes CHE110, CSE46D, and MEC106.

Figure 4. 13 Quality of delivery and MTTMarks in a selected three course code

Figure 4. 13 shows the quality of delivery with marks for three courses i.e. CHE110, CSE46D, and MEC106. In the above graph, the x-axis depicts the percentage of marks and the y-axis shows ratings from 1 to 5, and students scoring 25% marks have an average rating of 4.0, 4.4, 5.0 in respective course codes CHE110, CSE46D, and MEC106 and students with 40% marks had a rating of 3.6, 3.5, 4.1 in quality of delivery.

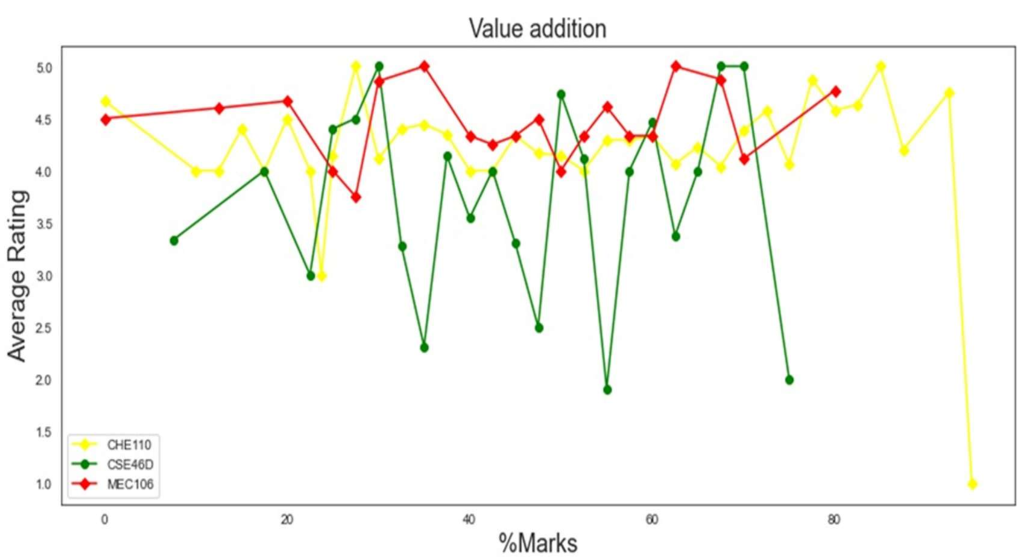

Figure 4. 14 Value addition and MTTMarks in a selected three course code

Figure 4. 14 shows a value of addition with marks for three courses i.e. CHE110, CSE46D, and MEC106. In the above graph, the x-axis shows the percentage of marks and the y-axis depicts ratings from 1 to 5, and students scoring 25% marks have an average rating of 4.1, 4.4, 4.0 in respective course codes CHE110, CSE46D, and MEC106 and students with 40% marks had a rating of 4.0, 3.5, 4.3 in value addition in course codes CHE110, CSE46D, and MEC106. These results are combined with ETT marks and assignments. Then finally CO attainment has been achieved. The above diagrams and work show that the correlation between students' marks and academic emotions can be checked at any point of the semester and help in the overall achievement of the students.

4.9.3 Maximum, minimum, and average rating of individual students along with course average rating

After checking the overall academic emotions of a particular course, the average rating of a particular student is measured to see whether a student is performing more or less than the course average. Table 4. 11 shows the average of individual parameters lecture-wise. The average quality of the content was 4.39, Examples/ Application was 4.35, Doubt clearing & Interaction was 4.32, Quality of Delivery was 4.29, and Value addition was 4.27. The maximum rating out of 5 was given to the quality of content i.e. 4.39 and the minimum rating was given to value addition which was 4.27 in a particular course code. Therefore, it is depicted that in a particular course out of these five academic emotions, students were highly satisfied with the quality of content and value addition having a scope for improvement. Moreover, from this data, each student's scope of improvement from the given five parameters can be identified and enhanced.

Table 4. 11 Average of each parameter in a particular lecture

Average Quality of content	Average of Examples/ Application	Average of Doubt clearing & Interaction	Average of Quality of Delivery	Average of Value addition
4.39	4.35	4.32	4.29	4.27

In Table 4. 11, the average of each parameter of academic emotion in a particular course was recorded. This average will help to see the student's rating in comparison to the average rating of each parameter.

Table 4. 12 Particular student's rating on five parameters with a minimum, student average, course average, and maximum rating

Parameters	Min	Avg	Course Avg	Max
Quality of content	4	4.4	4.4	5.00
Examples/ Application	3	4.2	4.3	5.00
Doubt clearing & Interaction	3	4.1	4.3	5.00
Quality of Delivery	3	4.2	4.3	5.00
Value addition	4	4.4	4.3	3.00

In Table 4. 12 Min (represents the minimum rating) and Max (depicts the maximum rating) given by the particular student in all the five parameters of academic emotions. Avg (i.e. students' average) rating of each parameter and Course average (i.e. overall) rating is the overall average rating of the course given by all the students of a class. It will give a clear idea of whether a student's average rating is matching with the course average rating or not. When a student's average rating is below the course average rating parameter-wise then there is a scope for improvement for the student. In Table 4. 12 students' average rating is satisfactory in the quality of content and in value addition for a particular student. At the same time, there is a scope for improvement in the example and application, doubt clearing and interaction, and quality of delivery.

In the following figure, an average rating of a course is calculated and the minimum, average, and maximum rating given by a particular student on each parameter is displayed.

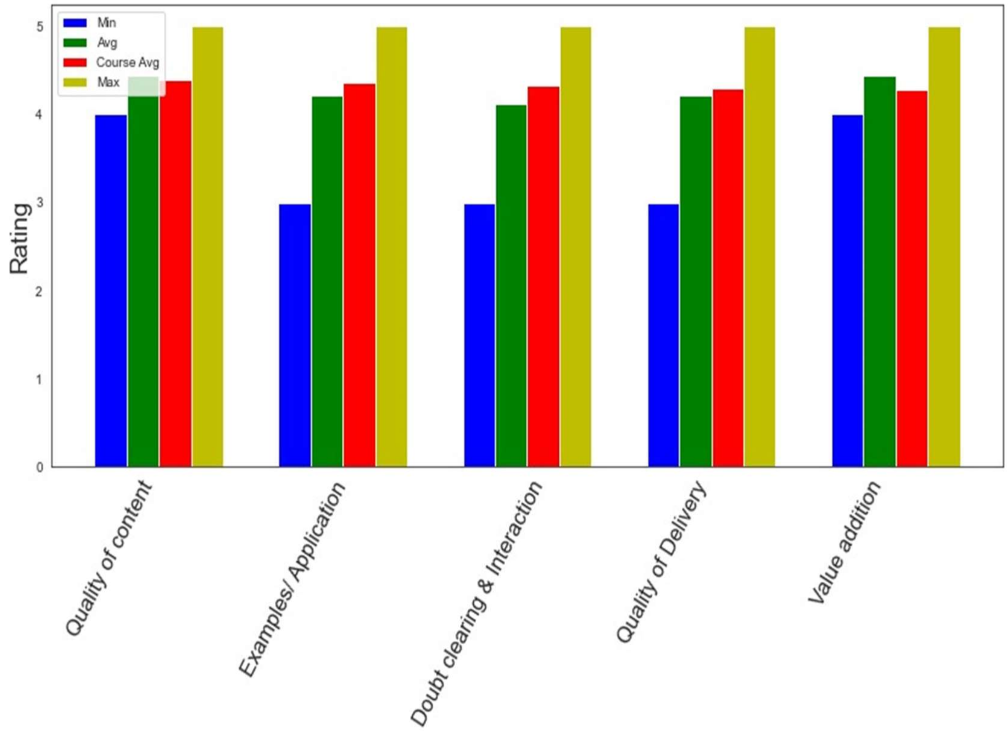

Figure 4. 15 Student rating in a particular lecture on all five parameters

Figure 4. 15 shows academic parameters on the x-axis and ratings on the y-axis. A single student's case was considered here. This can help to see individual students' average ratings and course ratings so that the scope of improvement in parameters can be identified and improved in the future.

4.10 Analysis

TERE framework helps identify various parameters of teaching-learning processes, if a faculty is teaching more than one subject then a comparative analysis can be made in which type of subject, the teacher is performing outstandingly i.e. in which subject all COs are performing above a threshold. In case overall attainment is below the threshold value in a particular subject then the average of academic emotion parameters constitutes the parameters in which the teacher needs to improve to get overall attainment. It is convenient to evaluate Teacher’s performance section-wise. If 50 students give their observations on a particular course 45 give a rating less than the school average and five students give a rating higher than the average school rating then it is need for teachers to work on requirements to improve overall attainment. More precisely, based on theory and practical subjects, clusters can be created based on 5 parameters to perceive in which set of parameters students perform well. Course-wise learning outcomes can be seen by summing up lecture-wise LOs. The aggregation Model for student performance has been generated based on the TERE dataset to get real-time results.

CHAPTER 5

BUILD AN AGGREGATION MODEL FOR SUMMING UP LECTURE WISE LEARNING OUTCOMES FOR EVALUATING UNIT-WISE AND COURSE-WISE LEARNING OUTCOMES.

5.1 Introduction

The system of student learning and academic emotions has recently been addressed seriously to re-engineer the teaching-learning process at all levels of education. There are two aspects of assessing the translation of knowledge during the teaching-learning process. One is a direct measure, wherein the learners are assessed based on scores they require in the tests, mid-term examination, end-term examination, etc., referred to as quantitative measures. The second is collecting academic emotions, which is how much learners participate and emerge throughout the class, which are referred to as qualitative measurements. In the current scenario, quantitative and qualitative learning outcome measurements are utilized separately without any associativity, which has been recognized as a key gap in the current study. An intelligent model is developed based on real-time data of students' quantitative performance and reviews collected as a qualitative measure from unhappy to happy. The proposed study curates the reason at a micro-level why the translation of knowledge is not happening for each class's learning outcomes and the aggregation model performs real-time assessment which is vital in the education system. There has been a mounting curiosity about the role of emotions in academic settings, principally in how emotions indicate student engagement and learning, why students experience emotions, how they affect learning engagement & achievement, and how institutions can use emotional components to engage and achieve [3]. Motivation, learning outcomes, and behavior are all affected by students' academic emotions. To assess academic emotions, a variety of methods have been produced and analyzed in a variety of studies. Emotion responses are defined by several parameters such as teaching methods, content, etc. Students can be empowered through teaching methods in supportive learning environments, and relationships feel contended when they participate in supportive learning [203].

Emotions like joy, optimism, and smugness are thought to help with both internal and external inspiration, as well as flexible learning strategies and self-regulation. Identifying how emotions like enjoyment, anxiety, boredom, etc. were studied and how these were measured by using self-report surveys is important [204,205]. Students' academic achievement will immediately improve after their emotional intelligence levels have been boosted. In education, emotional intelligence primes to improve student motivation to learn and improve academic achievement [206]. Emotional intelligence plays an important role in handling various problems for the prevention of activities related to mental health. It will have a positive effect on academics if student emotions are captured [207]. Therefore, an organized experimental study is required to determine the causal link between components of learning and the learner's affective processing during learning [118,131]. Moreover, in early studies, it has been seen that students experience more enjoyment and less anxiety and boredom if teachers exhibit better investigative skills [162]. While evaluating students' emotions in education in the twenty-first century, technology participation is pivotal. But it's critical to understand how and why emotions must be quantified in a variety of disciplines, including arithmetic, history, medicine, etc. Examples of emotions include feelings of accomplishment, fundamental feelings, social feelings, and others [116]. Academic control, value judgments, and achievement feelings have all been examined in complicated inspirational profiles [152]. Nowadays new expert teacher identity has appeared that is more akin to that of a "friend" than that of a commanding teacher. This negotiated teacher identity resulted in improved classroom interaction and positive emotional rewards [157]. The academic emotions and learning outcomes of the students both are necessary for their learning. Measuring academic emotions in any institution would firmly show deep insights into the student’s learning outcomes and represent the qualitative measure of learning. On the other hand, Quantitative measures of students’ learning can be measured on various parameters, which directly show the student’s learning outcome attainment. Scores achieved, contests, discussions, the authenticity of assessment, mid-term marks, end-term marks, assignments, etc. are generally used as quantitative measures [146,148].

Both quantitative and qualitative measures of learning play a crucial role in student learning outcomes. But these are considered distinct areas with their emphasis and represent the gap in the present context. Therefore, it is required to consider both aspects of student learning i.e. qualitative measures of learning and quantitative measures of learning to enhance the student learning outcomes. Moreover, capturing real-time student feedback about academic emotions will provide unbiased data for measuring the overall learning factors of the students. Both measures of student learning outcomes are enjoined in the present research work and it represents the prediction and aggregation model which enhances student learning outcomes. Two primary datasets have been used which have more than 11000 records of students' academic emotions in the first dataset and course outcome (CO) attainment data corresponding to the first dataset and in the second dataset more than 33000 records for students' academic emotions corresponding to course outcome (CO) attainment data. Qualitative and quantitative measures of learning are discussed to evaluate the student's learning outcomes from all the disciplines including engineering, architecture, applied sciences, etc.

5.2 Qualitative measure of learning

Academic emotions arise during education in a variety of academic situations, including during class, during assessments, while preparing or doing homework on their own, while learning in a group, and in other situations [208]. In recent years, researchers have become more concerned with emotion recognition. Things can be remembered and affected by emotions [209,210]. Various types of emotions have been researched that influence both students and teachers and many suggestions and insights have been drawn in the field of education [211]. Emotions are studied in education for three reasons: their impact on learning quality, students' physical and mental well-being, and their role in socialization. Five factors such as content quality, examples/application, doubt clearing & interaction, quality of delivery, and value addition all play a significant role during the class and are captured lecture-wise. These parameters play a significant role in student engagement and immersive learning during class. The content of the lecture is the foundation through which students learn new things, so the quality of the content is significant. The content is easier to comprehend when examples and applications are used. It will also provide a clear picture of the content and explain the purpose of the topic being discussed in class. If students' doubts are not cleared or solved during the lecture, it is necessary to interact with them regularly to clarify their understanding and eliminate their doubts. Quality in delivery and value addition also play a significant role during the lecture [137].

There was a need to design a system where students could leave feedback or capture feedback right after class. As a result, academic mapping of understanding is completed. Students can make a significant contribution to the school's/institution's improvement [138]. Feedback is important in education since it captures a student's feelings about learning. Where there is a gap in the mapping of student learning outcomes, feedback in terms of student academic emotions will aid in modification or improvement. It also demonstrates the importance of academic emotions in learning [151]. Emotional intelligence and its components can help to predict academic achievement. Emotional intelligence includes both Interpersonal components and intrapersonal components [147] and as a result, teachers must be emotionally intelligent so that their emotions do not interfere with their work [212]. The Teaching Effectiveness Rating Engine (TERE) is a real-time evaluation of what is going on in the lecture. If a student's feedback is taken as soon as the lecture is completed, it will highlight unbiased information about that lecture. Furthermore, it will bridge the gap between lecture delivery and lecture evaluation. TERE is a five-parameter rating system. This framework will assist students in feeling more satisfied by improving their academic emotions. Students' high ratings for all parameters indicate that they are satisfied in terms of their emotions. TERE has time table, Instruction plan (IP) master, Student report interface, and dashboard. Moreover, course outcomes (COs) are mentioned in the (IP) lecture-wise i.e. learning outcomes are evaluated from the micro to macro level wise. The proposed interface enables students to rate each parameter using smileys. Five parameters are used to measure students' learning outcomes on a 5-point Likert scale from happy to unhappy. In the proposed work CO attainment data is also stored on a scale of 3. The basic reason to scale down qualitative data is that quantitative data are stored on a scale of 3. So, in machine learning scaling is important and necessary to align data negating ambiguity. Ultimately, after feature scaling one data set is not going to dominate the other.

5.3 The Methodology used for the Qualitative measure of learning

Technology-rich learning settings in education are becoming more significant in the current century, and the emotions students feel in these situations are critical for their intellectual and sentimental learning gains. Therefore, it is necessary to recognize and quantify emotions in education [213].

Emotion regulation is a vital ability that can either benefit or hinder performance. Positive emotions include the enjoyment of learning, interest, and empathy for others, which are facilitated by successful emotion regulation, as a contrast to unfavorable reactions, such as unnecessary anxiety of failure or boredom, uncertainty, and frustration during difficult problem-solving [214] Negative emotions are complicated and, their impact on content engagement varies depending on perceived control and worth [39].

TERE framework represents parameters used to capture students' academic emotions. Figure 5-1 shows the qualitative model of learning outcomes. The total number of COs varies in the different subjects. Indeed, this variation took place in theory or practical subjects.

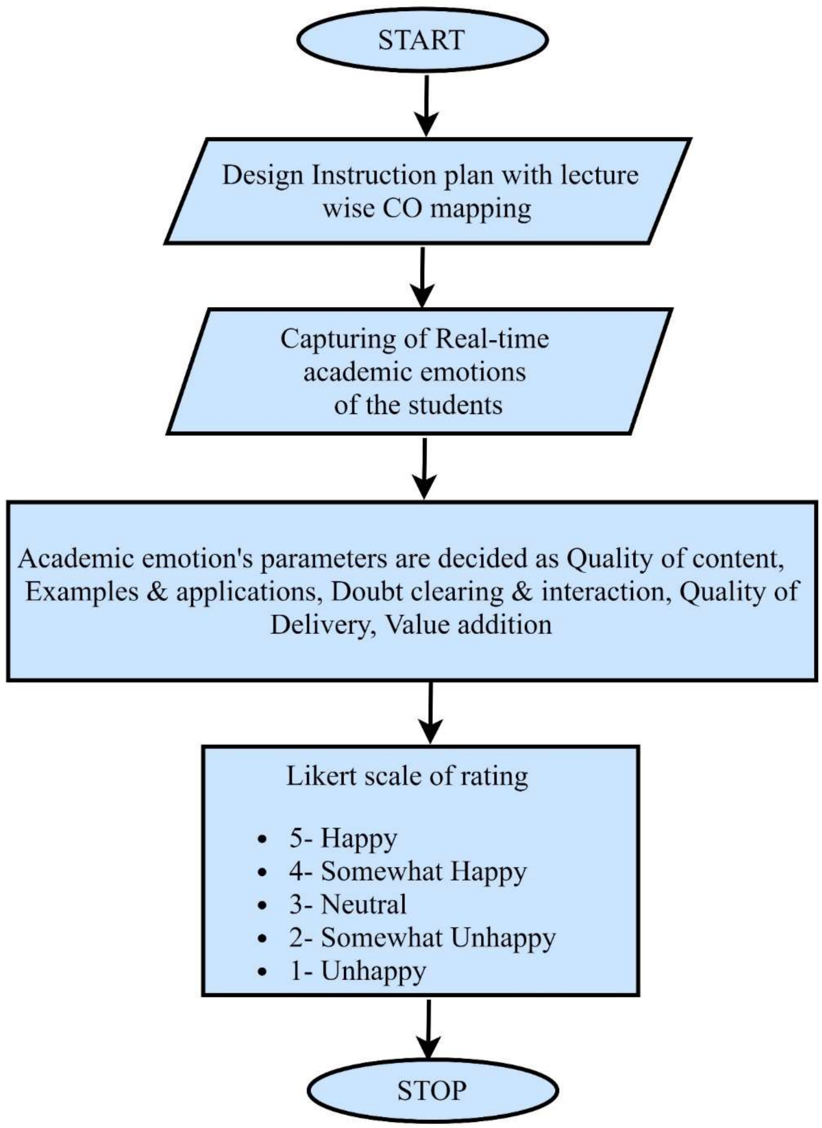

Figure 5. 1 Qualitative Model.

Figure 5. 1 shows the qualitative model of learning outcomes. Furthermore, various practical or theory courses can have different numbers of COs. Lecture-wise COs are mapped to the instruction plans of each respective subject. Students give feedback on five parameters representing academic emotions.

5.4 Pseudo code to scale down Qualitative Measures

Step 1: Identify the CO.

Step 2: Capture all the lectures corresponding to the selected CO in which it is participating.

Step 3: For those lectures, there must be a value given by students from 1 to 5 Likert scale for each parameter i.e. quality of content, example & application, doubt clearing and interaction, quality of delivery, and value addition.

Step 4: These parameters are measured on a 5-point Likert scale where 1 denotes unhappy, 2 refers to somewhat unhappy, 3 states neutral, 4 refers to somewhat happy, and 5 stands for happy.

Step 5: Sum up all the values of a particular parameter for all lectures for this CO and take its average.

Step 6: Repeat the same for other parameters and take their average too.

Step 7: For each parameter average out all the lectures in which that CO appears divide by 5, and multiply by 3.

Step 8: This will scale it down to 3 and would align it to quantitative attainment.

CO attainment data is also stored on a scale of 3.

5.5 Quantitative measure of learning

Students' assessment grades were used to assess their learning outcomes. The concentration is on how learning outcomes are alleged and applied at various points for assessing students' grades [215].

Curriculum alignment, or assessing the educational program's defined learning outcomes, is the best assessment mode. CO attainment is the measure of quantity-oriented learning outcomes which represents quantitative data about students learning [145]. Different assessment formats depend on the genre and academic discipline

[146]. Engineering education is highly structured and driven by knowledge attributes, course outcomes, and program outcomes with a focus on student self-learning. Pedagogical strategies for achieving course outcomes vary by course, active learning techniques, and assessment achievement is calculated by a student's response to their performance. Advancing the assessment of undergraduate and graduate student learning outcomes is essential for the upcoming higher education [148]. In the proposed work, the quantitative model consists of COs which are a measure of learning outcome based on the performance of the learner in the assessment tools like class assignment, mid-term and end-term evaluation. Questions given in-class assignments, mid-term, and end-term are mapped with one or more COs. The questions designed will be associated with appropriate COs and the performance of students for a particular question would be a measure to understand how much learning outcome has been attained for an associated CO.

5.6 The methodology used for the Quantitative measure of learning

Figure 5. 2 depicts the quantitative model of the learning outcomes. The quantitative model represents the marks attained by the students and all the questions are mapped with one or more COs. Then weightage of each CO is calculated.

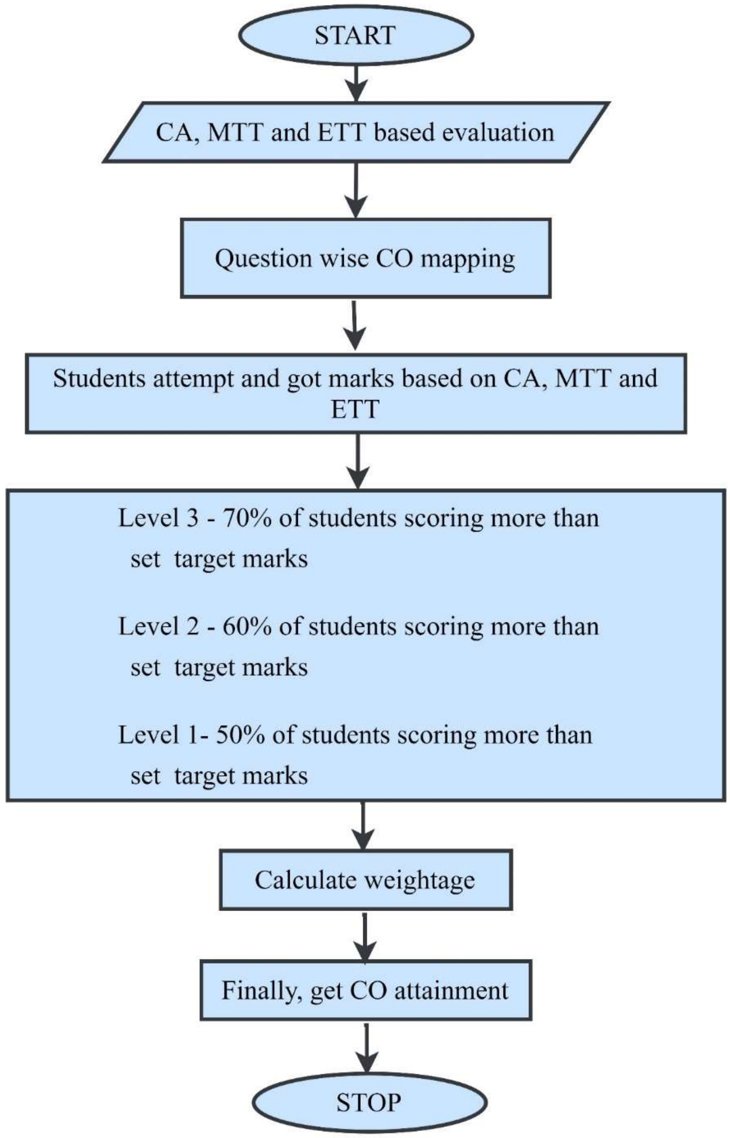

Figure 5. 2 Quantitative Model

In Figure 5. 2 quantitative assessments of student learning have been explained in detail. The quantitative measure includes mid-term, end-term, and assignment marks.

5.7 Proposed Research Methodology

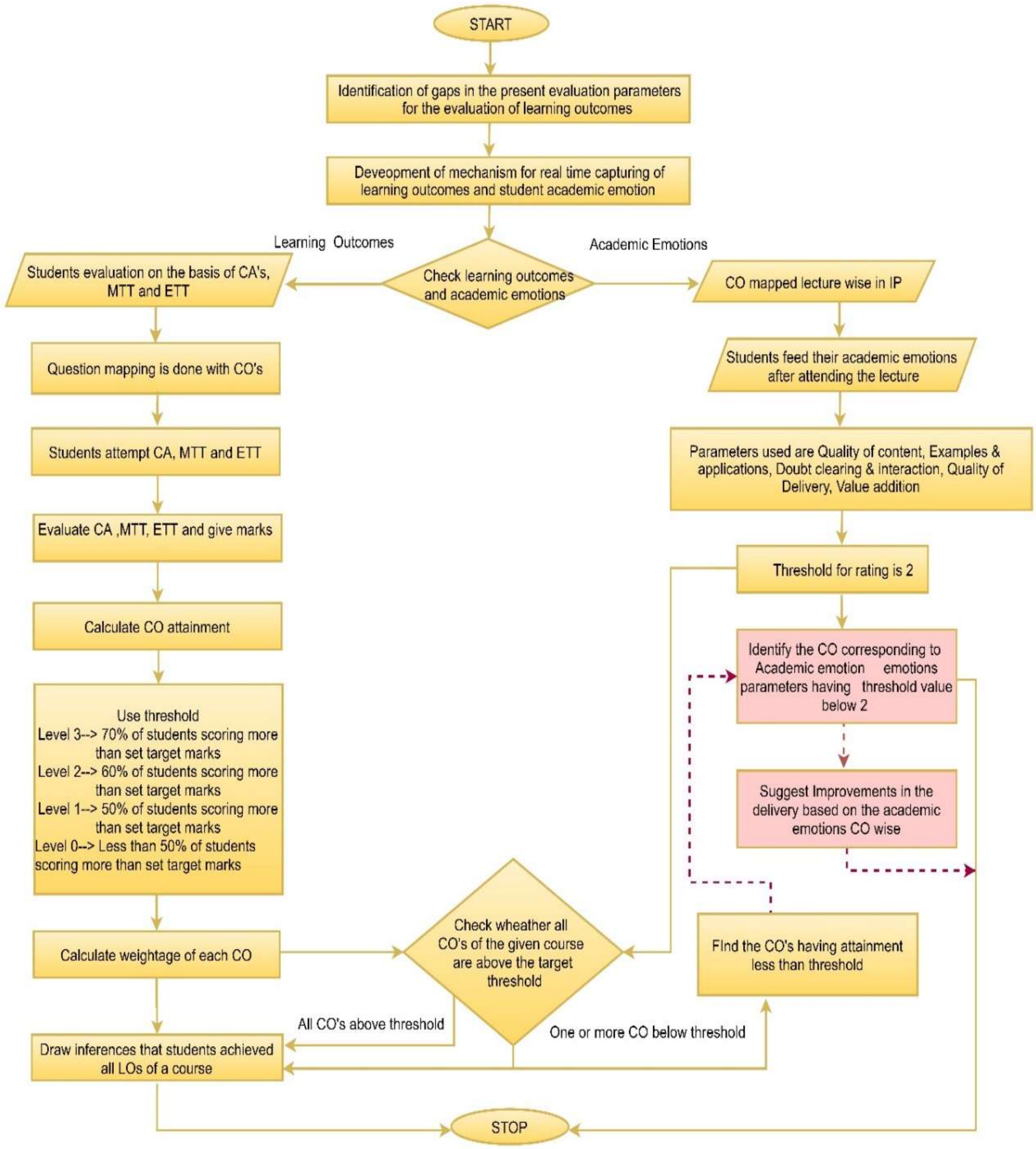

Figure 5. 3 The Proposed methodology to draw inferences based on CO attainment

Figure 5. 3 shows the combined model of qualitative measure and quantitative model and the following is an explanation of the proposed model in steps.

5.8 Pseudo code to draw inferences based on CO attainment

Step 1: Check whether all COs of a given course are above the threshold. If yes then draw Inferences that the student achieved all learning outcomes. If not, go to step 2.

Step 2: Identify CO below the threshold i.e. least attained CO according to the threshold.

Step 3: Check lecture-wise where these CO (COs) are participating in a course.

Step 4: Identify the least performing academic emotion corresponding to the CO (or COs).

Step 5: Suggest improvement in delivery based on academic emotion CO-wise.

5.9 Proposed intelligent Mechanism for Truthful assessment of Learning

To capture the students' academic emotions, a novel framework TERE is used, and a primary data set is generated using five parameters on a five-point Likert scale. This framework captured a huge dataset from a student from pan India with more than 33000 records and 970 courses. Qualitative data is captured using this framework and the entire data is curated to keep the secrecy and confidentiality of students intact. In the previous research [216], it has been discussed that students' grades reflect their learning outcomes and other parameters like increasing or decreasing learning trends.

Similarly, the second primary data set of CO attainment was generated based on marks attained by the students in the assignment, mid-term, and end-term. CO attainment is a step-by-step procedure for generating a CO master file, course CO mapping, CO mapping with CA midterm and end-term, identifying CO level from 1(=low) to 3(=high), Calculating CO weightage, and finally, CO attainment has been found. These datasets are generated on the marks achieved by the students from various streams of engineering, architecture, management, applied sciences, etc.

In the proposed work, courses that have COs below the threshold are identified, and then the average academic emotion parameter was checked for lectures corresponding to that CO. Then two academic emotions scoring the lowest were identified as primary and secondary suggestions. The same process is repeated for the other CO having attainment of less than 2. On the other hand, courses with CO attainment above the threshold are used to draw inferences.

5.9.1 Algorithm for selecting which academic emotion responsible for pulling down the Course Attainment

STEP 1 Defining List for storing values

table = [] #Empty List for Storing Academic Emotion as well as corresponding CO and Course

Satisfactory_CA = [] #List for storing those Courses in which CA is greater than the threshold (i.e. 2)

STEP 2 Creating a Function that would return the particular information corresponding to each course for Each CO

Function code

Info (): #Defining Function

Selected_data = data where CourseAttainment is < 2 and CourseCode is as Per User's Choice

rows = [] #for storing the index of rows

cols # List of Academic Emotions' Name

res_col = [] #List to store index corresponding to Academic emotion

flag=True # It would be used for checking which course has above threshold Course Attainment

STEP 3 Identification of the courses having overall attainment below a threshold.

for i=0 to total_no._of_rows:

flag=False #inside Loop means we have data for the course which have less Course attainment value

STEP 4 Storing courses in the Satisfactory list or the improvement list

1. Storing index of minimum value of academic emotion given by students in a variable.

2. Appending col index as in res_col list as per Selected Data

3. Appending row index in which we have Course Attainment value is less than 2.

Check if the Flag is true:

Append Course to Satisfactory_CA list

or each row and column in (row and col):

Appending Data as a dictionary in the Table List created.

5.10 Prediction Model

There are two ways of measuring learning outcomes i.e. Quantitative measures and Qualitative measures. Quantitative datasets are supplemented by qualitative assessments. It provides a more complete view of learning outcomes [217]. In the present work, quantitative and qualitative data are used together, thus depicting a comprehensive picture of learning outcomes. Students' academic emotions are revealing qualitative measurements and indicators. On the other hand, quantitative measures take longer to collect and focus on parameters like mid-term, end-of-term, and assignment grades, among other things.

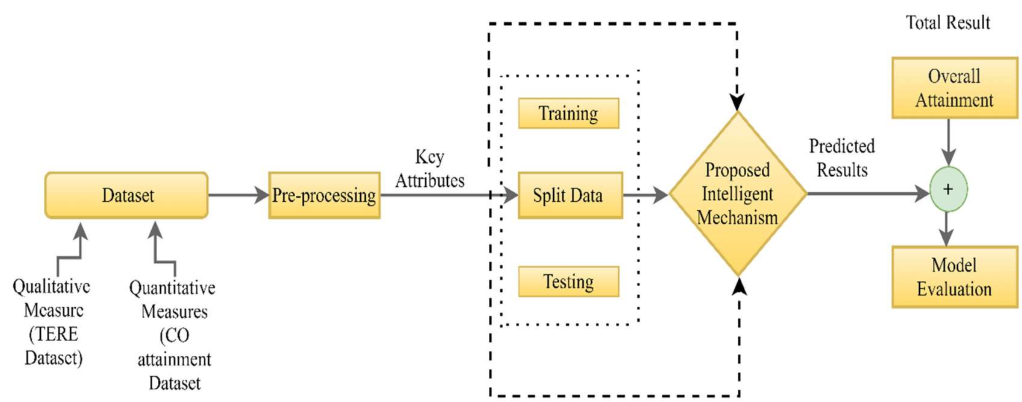

Figure 5. 4 Proposed Prediction Model

Figure 5. 4 depicts the proposed prediction model. Here academic emotion (qualitative measures) enjoins with a quantitative measure to get the true picture of the learning outcomes. In many existing studies in different fields, qualitative and

quantitative aspects were considered [218,219]. Similarly, in the proposed model combination of both qualitative and quantitative measures has been considered.

Educators should conduct consistent, intervallic evaluations designed in a course and ensure that learning outcomes are of equal difficulty. Different assessment formats along modes are used and students need to perform consistently to satisfactorily attain learning outcomes [220]. Despite the advancement of learning outcomes approaches in higher education, there is little evidence of its use by academics. It also emphasizes the need for more research to deliver the indication needed to clarify and rank for academics the multiple factors that influence how learning outcomes are enacted [142]. Furthermore, numerous factors influence students' perceptions of assessment quality, such as their learning methods and outcomes [221].

In the proposed model continuous assessment is performed by calculating COs at the micro-level. The proposed intelligent mechanism creates the ideal predictive model by using machine learning. In this approach, many base models like linear regression, decision tree, random forest, and ridge regression are combined to get better performance of the model. R-square, MSE, RMSE, and MAE have been calculated for the intelligent mechanism. Class assignments, mid-term and end-term, and CO attainment can be calculated after the lecture. The same will be compared with academic emotion and thereafter, machine learning approaches are used to evaluate whether learning outcomes are achieved or not. It also recommends whether any improvement/changes are required or not.

5.11 Proposed Aggregation Model for unit-wise and Course-wise learning outcomes

Raw data is used to create machine learning features, which act as an input to a Machine Learning model. In the proposed work SQL queries have been used against both datasets (i.e., qualitative and quantitative). These datasets are joined using common features as per the requirement of the SQL. Then, the Aggregation model is used to get real-time predictions about the student learning outcomes.

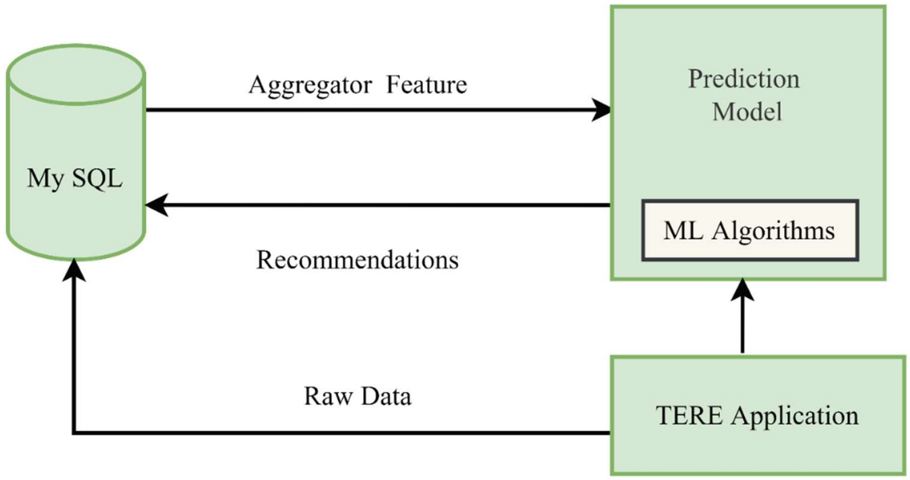

Figure 5. 5 Proposed Aggregation Model

In Figure 5. 5, the TERE applicator generates raw data and it is transferred to MySQL at the same time it is transferred to the prediction model. Aggregated features are given to machine learning algorithms and query recommendations are generated. It can be single or multiple depending upon the data. Then this data is transferred to MySQL. This cycle will work continuously and aggregated features are transferred to machine learning algorithms every semester and inferences are drawn based on aggregation features.

Further, based on the dataset available with SQL, real-time prediction is made. The real-time prediction of student learning outcomes depends upon the qualitative and quantitative datasets. This model works as a generalized model because inferences can be drawn every semester on a real-time basis and a qualitative measure of learning outcome can be combined with a quantitative measure of learning outcome.

5.12 Result of the Aggregation Model

The aggregation model depicts the result using machine learning. This model gives the results by combining both datasets. Table 5. 1 depicts after combining both databases on the conjoint field course.

Table 5. 1 CO below a threshold value

CO's	Quality of Content	Example/ Applications	Doubt clearing and interaction	Quality of delivery	Value addition	Course	Course-Direct Attainment
CO1	2.72	2.66	2.64	2.6	2.7	CSE202	1.8
CO3	2.64	1.06	2.60	2.5	2.6	CSE202	1.7

Table 5. 1 shows the result that in course CSE202, two COs have course attainment below a threshold value, i.e., CO1 and CO3. The threshold value is 2, and course attainment is 1.8 in CO1 and 1.7 in CO3 in the course CSE202. Therefore, these COs are placed in the output frame. The threshold value is validated by using the K-means algorithm in machine learning.

5.13 Discussion

Various existing studies related to the learning outcomes are accepted and published. Most of these studies are either related to the qualitative measure of learning or the quantitative measure of learning. The qualitative measure of learning includes parameters like self-regard or determination, emotional self-awareness, compassion, social concern, anxiety tolerance, enjoyment, hope, confidence, enthusiasm, pride, anxiety, boredom, interest, irritation, nervousness, anger, quality of content, etc.

Even in e-learning enjoyment, boredom, and anxiety, etc. are practical implications for the emotional design of learning and developing a more complete theory [122]. According to the findings, students who are enthusiastic about their studies are more likely to participate in academic procrastination [154]. Students' creativity, motivation, curiosity, performance, and social cohesiveness can all benefit from positive emotions [155]. Emotional intelligence and its aspects are statistically significant predictors of academic performance in students' where intrapersonal mode is a positive and interpersonal mode is a negative predictor. With the support of distinct learning tools, the qualitative output of learning increased with time, and learners achieved considerable gains in the learning process [222].

Qualitative assessment methodologies and theoretical foundations derived from qualitative research may help us promote a more holistic picture of the student college experience and, in certain situations, give a more thorough story than quantitative evaluation methods alone [223].

On the other hand, after going through a detailed literature survey, it has been identified that quantitative measures of learning outcomes considered parameters such as scores achieved, quizzes, tests, interactive videos, discussions, number of files viewed, questionnaires, effects of assessment on learning, justice of assessment, conditions of assessment, the authenticity of assessment, oral presentation, interviews, etc. [224]. Quantitative learning measures are centered on the score achieved by the students in mid-term, end-term, assignments, etc. The previous studies either included the measure of learning outcomes or the measures of a qualitative measure of learning. To gather both numerical (quantitative) and descriptive (qualitative) data, a mixed-method strategy might be utilized. The goal of this strategy is to ensure that the problem is thoroughly examined by gathering both quantitative and qualitative data [225].

The proposed study includes prediction and aggregation models that have been used in both the qualitative and quantitative measures of learning. Here, qualitative measures (academic emotion) are captured using 5 parameters i.e. quality of content, example, and application, doubt clearing and interaction, quality of delivery, and value addition in real-time. A quantitative measure of learning is measured on scores achieved by the students in evaluation tools like mid-term, end-term, and assignments. This novel model identifies the reason why translation in the teaching-learning process is not happening and the solution is also recommended. This model considers both sides of teaching-learning and delineates the correlation of these measures for recommending the resolves for underperformance. A qualitative measure of learning is appended with a quantitative measure of learning to improve the delivery based on academic emotion CO-wise. The threshold in the proposed model is validated as 2 by the KNN algorithm of machine learning. Predicted results are seen based on the overall attainment and model evaluation. Inferences are derived to improve the learning outcomes of the students by improving the parameters corresponding to their academic emotions.

5.14 Conclusion

In the present scenario, qualitative and quantitative measures of learning outcomes are treated separately, and this research identifies it as a major gap. In this research work first, the academic emotions of the students were captured based on the unique framework Teaching Effectiveness Rating Engine (TERE). A novel aggregation model is proposed to evaluate the learning outcomes and improvements are suggested by logically enjoining the qualitative reviews given by the students on the real-time and quantitative performance of the students. The aggregation model works as a generalized model because inferences can be drawn every semester on real real-time basis and a qualitative measure of learning outcome can be supplemented with a quantitative measure of learning outcome.

CHAPTER 6

PROPOSE AN INTELLIGENT MECHANISM FOR TRUTHFUL ASSESSMENT OF LEARNING OUTCOME OF A COURSE BASED ON MICRO PARAMETERS OF LECTURE-WISE AND UNIT-WISE LEARNING OUTCOMES ATTAINED

6.1 Introduction

Assessment is the prime component of assessing students' learning in higher education; it motivates students to improve by offering them information about their progress as well as information about the planned learning goals and how they might be met [226] [227] [228]. Assessment should be part of effective planning of teaching and learning. The focus of assessment should be on how students learn. Assessment quality views among students are connected to their learning techniques and learning outcomes [229]. Given the importance of assessment in learning, educational program performance is determined not only by assessment itself but also by assessment quality[230]. Assessment depends upon more than one evaluation practice like scores achieved in mid-term, end-term, and assignment, feedback, etc. This represents the quantitative measure of learning [231]. But to understand in-depth the students learning students' academic emotions need to be measured. The easiest way to evaluate and support students' learning is to capture feedback on learning outcome parameters. The role of cognitive and motivational parameters is better understood than emotional assessment. But academic emotions along with their feedback play an important role in students' learning. But, it has not got the same level of attention[232]. Emotions are very important in capturing feedback as other parameters like motivation, social factors, cognitive skills, etc. but their role is recently been recognized. Therefore it is crucial to consider both sides of education. After going through a detailed literature survey, a gap has been identified that in most studies, only one aspect of students' learning outcomes is considered [233].

The proposed work addresses both qualitative and quantitative measures in learning and enhances student learning outcomes. It is seen in existing human behavior studies that emotion has piqued the interest of academics in machine learning. To detect important emotional states numerous classification approaches have been examined [234]. Machine learning algorithms can be used to optimize various emotions of the students such as joy, sadness, fear, anger, surprise, disgust, neutrality, and help in the identification of the gaps due to which learning outcomes are not achieved [235]. Moreover, the quality of assessment perceived by students is linked to their learning styles and outcomes. Impacts of evaluation on education, the integrity of assessment, testing settings, translation of test scores, assessment authenticity, and assessment credibility are six factors associated with students' assessment quality ratings. The role of Machine Learning has increased in education and other sectors. Therefore it is used in the proposed work.

6.2 Motivation

In Machine Learning, algorithms that increase their performance over time are designed and implemented. The type of data has a considerable influence on the choice and performance of a learning algorithm used to describe the task to be done. Learning will be unsuccessful if the data lacks the statistical regularity that machine learning algorithms rely on. Theoretically, it is possible to generate fresh data from old data in a way that promotes statistical regularity but because it is so challenging, an automatic method is impractical [232] [236]. However, if the data is suitable for machine learning, the effort of discovering regularities can be simplified and accelerated by removing data elements that are irrelevant or repetitious to the task to be learned. This is known as feature selection. The method of feature selection is well-defined, practically automatic, and computationally tractable, in contrast to the process of creating fresh input data. Feature extraction is the process of converting raw data into numerical features that may be handled while keeping the information in the original data set. It gives better results than utilizing machine learning on raw data directly. Feature selection and sampling are two ways that allow regular machine learning algorithms to be applied to big databases. Both methods, feature selection by selecting the most significant features of the data and sampling by identifying representative instances, lower the size of the database. Here, primary datasets are used with machine learning to provide quick and real-time results. Once the category of the data is identified it will help in algorithm selection When data is labeled it comes under supervised learning. On the other hand, when data is not labeled it comes under unsupervised learning e.g. in the case of continuous and labeled datasets regression algorithms are applied. Classification algorithms of machine learning are applied when data is labeled and discrete. Unlabeled and continuous data is handled using clustering algorithms of machine learning. Whereas, association algorithms are implemented if, data is unlabeled and discrete. Therefore, it is efficacious to use machine learning and the use of Machine Learning in education will enhance student learning outcomes and assessment.

6.3 Significance of Machine Learning in Education and Learning

Information about the teaching feedback can be preserved and used in many stages of learning where machine learning platforms will help in gathering and collecting the data and evaluating results from these students based on academic emotions. Learning is affected by environmental factors, intelligence level, interests, hobbies, etc. Machine learning has easy preservation results and high efficiency. With the help of machine learning, a human knowledge base can be improved [237] [88] [238]. The algorithms like random forests, regression trees, and classifiers are used in the prediction of student attendance, and dropout and to check their initial learning [239]. Similarly, the dataset in the TERE framework is handled by using machine learning. Figure 6-1 depicts the links of machine learning to various ideas in data science and artificial intelligence. Statistics are used in data mining to extract hidden information (patterns) from raw data [240], which provides the exact information as per requirement. Further machine learning process needs to be followed for feature engineering, training, testing, and algorithm design.

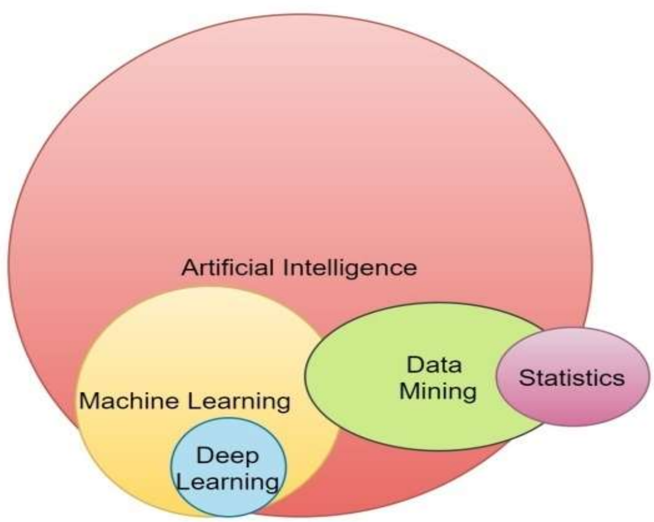

Figure 6. 1 Relationship of Machine learning with other fields

Machine learning algorithms are applied to the TERE and CO attainment datasets to check the correlation between the MTT marks, ETTMarks, overall CO attainment, and academic emotions.

6.4 Machine Learning Process and Paradigm

In machine learning processes data can be of a large or small size depending upon the problem for which it is collected to give input to the algorithm. It may contain noise and numerous features therefore it requires data cleaning and feature selection by using various techniques. The choice of an algorithm, model selection, and training of the dataset on given parameters needs to be completed to find accuracy, precision, and recall values tested against unseen data [241].

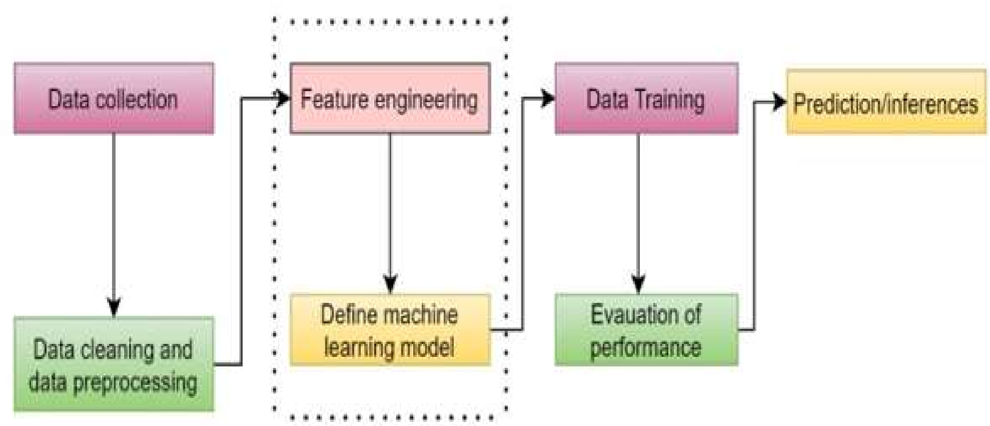

Figure 6. 2 Generic Machine Learning Model

The generic machine learning model is depicted in Figure 6. 2 which includes data collection, cleaning, feature engineering, training of data, and then at last prediction will be evaluated. In this work, the TERE dataset has been used which captured and pre-processed the real-time academic emotions of the students on a micro level i.e. lecture-wise. The following subsection will explain the machine learning paradigm. There are four types of machine learning algorithms: supervised, unsupervised, semi-supervised, and reinforcement learning. In supervised learning, a collection of training data or labeled data is provided with known structure and outcomes, and a machine learning model is trained to recognize patterns in the data and predict the results [242]. Conversely, unsupervised learning methods learn the structure from the data itself without the need for prior labeling [243]. The TERE dataset is a labeled dataset that has input variables and output variables.

6.5 About Data Sets

The World Wide Web offers a variety of forums for users to share their opinions and feelings on an event, product, location, or brand, among other things. Social networking sites, discussion forums, and blogs have a significant impact on both the supply and buyer sides. Feedback is critical since it conveys the student's feelings about learning. Where there is a gap in the mapping of student learning outcomes, feedback in terms of student emotions will aid in adaptation or improvement.

TERE is a granted Indian copyright with **copyright number SW-14125/2021**. The academic emotions of the students are stored in the TERE dataset. TERE data set and CO attainment datasets have been captured for two academic sessions i.e. Fall and Spring are used for training, testing, and validation. Description of the TERE dataset and CO attainment datasets have been given below. The Primary values are derived based on this dataset. Instances of both datasets are given in the tables below:

Table 6. 1 Description of the TERE dataset

Description	Value
Name of dataset	TERE
Number of Entries	13000
Number of courses	970
Source	UNIVERSITY (LPU)
Session	19201
Year	2019

Table 6. 2 Description of the TERE dataset1

Description	Value
Name of dataset	TERE
Number of Entries	11000
Number of courses	590
Source	Lovely Professional University
Session	19202
Year	2019

Table 6. 3 Description of CO attainment dataset

Description	Value
Name of dataset	CO attainment
Number of COs and courses	115 COs corresponding to 25 courses
Source	UNIVERSITY (LPU)
Session	19201
Year	2019

Table 6. 4 Description of CO attainment dataset1

Description	Value
Name of dataset	CO attainment
Number of Entries	50 COs corresponding to 10 courses
Source	UNIVERSITY (LPU)
Session	19202
Year	2019

Academic emotion parameters are multi-valued parameters used for measuring learning outcomes. These parameters are measured on a 5 Likert scale as given below

1 - Unhappy.

2 - Somewhat Unhappy.

3 - Neutral.

4- Somewhat happy.

5- Happy

6.6 Preprocessing of the datasets

Preprocessing was done on both datasets before the execution of the proposed model. During pre-processing of the data missing values, noisy data can be identified and handled as per the values given in the dataset, and normalization of data needs to be done. Outliers can be swept out using univariate and multivariate analysis. It has been found that the given dataset has some outliers and is handled properly before further analysis. Feature engineering and feature scaling were also performed on the given dataset and datasets were combined. Both the TERE dataset and CO attainment datasets are collected and uploaded into the Jupyter Notebook in Python as shown in the tables above i.e. Table 6. 5 and Table 6. 6. Machine learning algorithms like Decision Tree (DT), SVM, Random Forest, Naïve Bayes, etc. can be used to measure student learning outcomes and it can be identified whether learning outcomes are achieved or not [217].

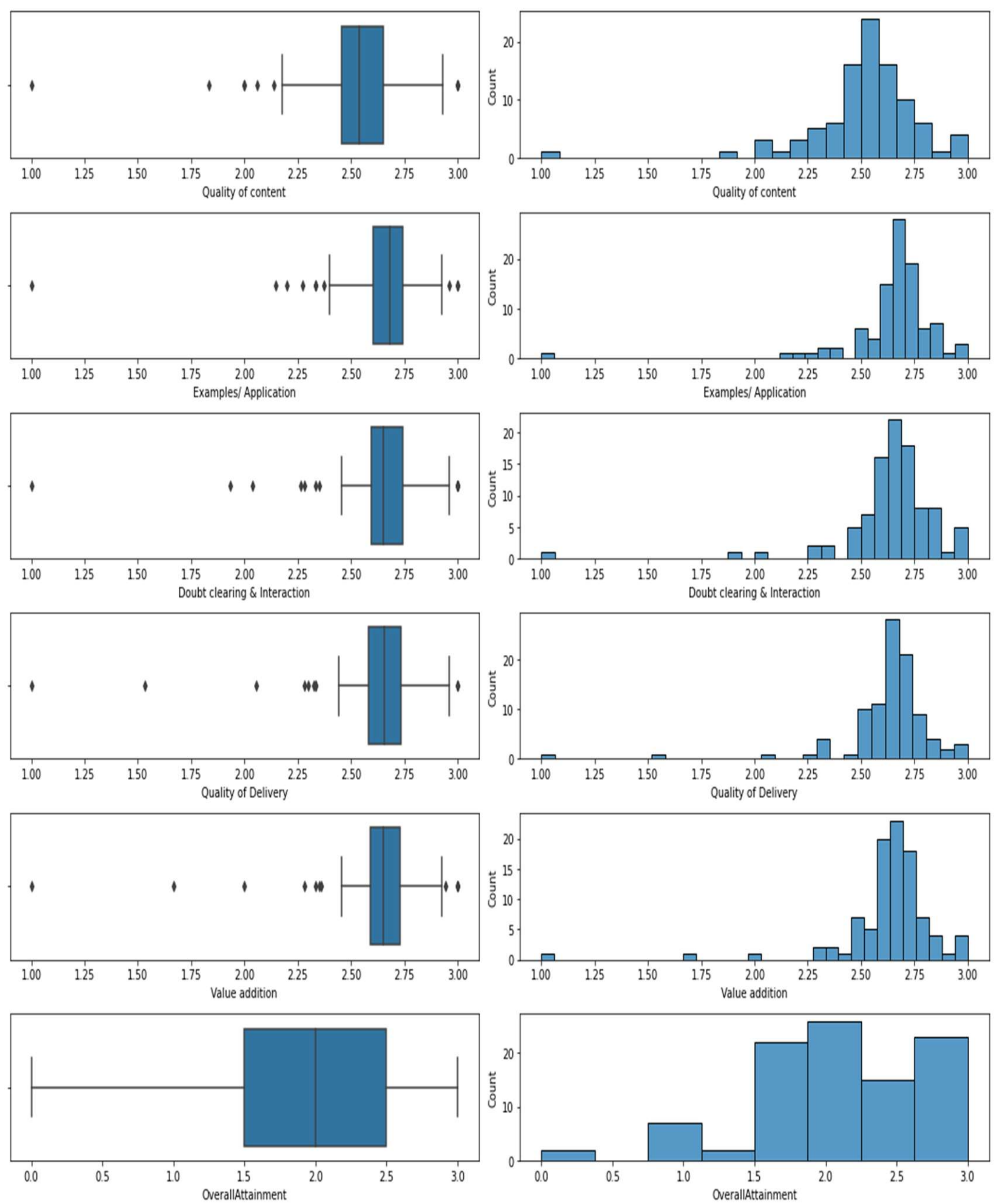

Figure 6. 3 Identification of outliers using a box and scatter plot

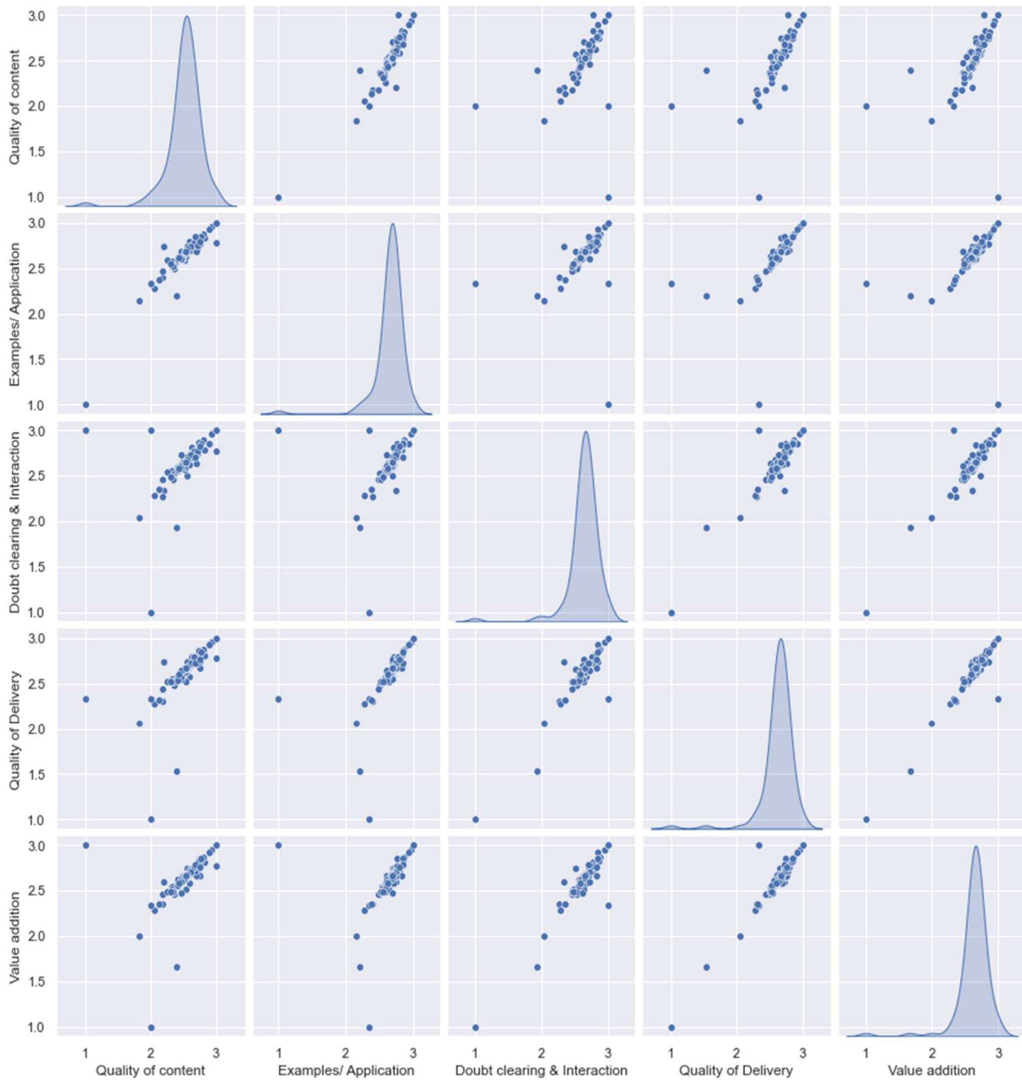

Figure 6. 4 Multivariate Analysis

Linearity can be seen in any two features given in a dataset. Feature engineering and feature scaling are also performed on the given dataset. This data is systematically distributed with no skewness and follows a bell shape. Here most of the values cluster around the central region. Standard scaling has done the feature transformation in the given dataset and it converted the feature where the mean is 0 and the standard deviation is 1.

6.7 Feature Selection

To prevent overfitting on the training set, several algorithms utilize bias to generate a basic model that works well on the training data [244]. As a result of this bias, algorithms usually prioritize a limited number of predictive characteristics over a huge number of features. When features are combined properly, results are predictions of the class label. Learning is more difficult during the training phase if there is a huge amount of duplicate and unsuitable data, or if the input is noisy and inaccurate [219] [245]. Finding and removing unnecessary and duplicate data is known as feature selection. It decreases data dimensionality and may allow learning algorithms to work more quickly and efficiently. One of the benefits of feature selection for learning is that it reduces the quantity of data necessary to achieve learning, an increase predicted accuracy, more compact and understandable learned knowledge, and shorter execution times.

Three primary methods are utilized for feature selection in supervised learning: the filter, embedded, and wrapper methods. However, filter approaches usually use less computationally expensive algorithms to evaluate the performances of feature subsets. Similarity metrics like Pearson's Correlation Coefficient (PCC), Euclidian distance, and Mutual Information (MI) are some often used heuristics that may be used to determine a feature set's relevance and redundancy. The filter model considers the correlation between the features and predictor [246] [247]. A feature can be regarded as irrelevant if it is conditionally independent of the class labels. It essentially states that if a feature is to be relevant it can be independent of the input data but cannot be independent of the class labels i.e. the feature that does not influence the class labels can be rejected. Feature correlation plays an important role in determining unique features [248].

In this work, two feature selection methods have been used that is correlation and Mutual information. Various features like quality of content, examples and application, doubt clearing and interaction, quality of content, and value addition have been used and Overall attainment is used as a predictor to check the correlation among them. Here, correlation is the measure to check the association between two or more variables. Figure 6. 11 depicts a heatmap that shows, there is a high correlation between input and dependent variables. The logic of using correlation for feature selection is to finalize the features that are highly correlated with the target variable.

Here, a few input features are highly correlated to each other i.e. more linearly dependent, therefore one can be dropped. Due to a limited number of features, all the features have been kept. These features are also correlated well with predictor.

After feature selection, only five parameters are used to represent the student's academic emotions i.e. quality of content, example and applications, doubt clearing and interaction, quality of delivery, and value addition. The teaching effectiveness rating engine (TERE) is a real-time review of what is happening in the classroom. If the student's feedback is collected as soon as the lecture is over, it will provide neutral information regarding that lecture. Furthermore, it will close the gap between lecture delivery and lecture evaluation.

Table 6. 5 TERE dataset

Course Code	CO's	Quality of content	Examples/ Application	Doubt clearing & Interaction	Quality of Delivery	Value addition
CSE202	CO2	5	5	4	5	5
CSE202	CO2	5	4	4	4	4
CSE202	CO2	5	5	5	5	5
CSE202	CO1	5	4	4	4	4
CSE202	CO1	4	4	4	4	4
CSE202	CO1	5	5	5	5	5
CSE202	CO3	4	4	4	4	4
CSE202	CO3	4	4	4	4	4
CSE202	CO3	4	4	4	4	4
CSE202	CO3	4	4	4	4	4
CSE202	CO4	5	5	5	5	5
CSE202	CO4	3	3	2	2	1
CSE202	CO4	5	5	5	5	5
CSE202	CO4	5	5	5	5	5
CSE202	CO5	5	5	5	5	5
CSE202	CO5	5	5	5	5	5
CSE202	CO5	5	4	4	5	5

Table 6. 7 shows the quality of content, for example/application, doubt clearing & interaction, quality of content, and value addition of various COs in course code CSE202. These parameters are captured on five Likert scales. The corresponding dataset used is the CO Dataset. It contains course code, course outcomes, and overall all attainment i.e. course attainment.

Table 6. 6 CO dataset

Sr. No	Course Code	CO's	Course Attainment
1	CSE 202	CO1	1.8
	CSE 202	CO2	3.0
	CSE 202	CO3	1.7
	CSE 202	CO4	2.0
	CSE 202	CO5	2.9
2	CSE 50D	CO1	2.77
	CSE 50D	CO2	2.71
	CSE 50D	CO3	2.71
	CSE 50D	CO4	3.00
	CSE 50D	CO5	1.50
	CSE 50D	CO6	3.00
3	CSE32D	CO1	1.78
	CSE32D	CO2	2.71
	CSE32D	CO3	2.50
	CSE32D	CO4	1.90

Table 6. 8 describes the dataset which shows CO-wise Course Attainment for various course codes.

Table 6. 9 depicts the dataset after scaling both datasets at the same level and combing. In this table course, CSE202 has depicted which shows academic emotions and CO attainment lecture-wise of that course.

Table 6. 7 Combined dataset

CO's	Quality of Content	Example/ Application	Doubt clearing and interaction	Quality of delivery	Value addition	Course Code	Course Attainment
CO1	2.72	2.66	2.64	2.6	2.7	CSE202	1.8
CO2	2.43	2.47	2.36	2.3	2.4	CSE202	3.0
CO3	2.64	1.06	2.60	2.5	2.6	CSE202	1.7
CO4	2.70	2.63	2.60	2.6	2.6	CSE202	2.0
CO5	2.59	2.64	2.61	2.6	2.5	CSE202	2.9

Table 6. 9 enjoins both datasets i.e. table 6. 7 & Table 6. 8. It reflects CO-wise course attainment & academic emotions for a particular course code. It shows the machine-learning implementation of the proposed dataset. First of all, both the data sets were collected and uploaded to the Jupyter Notebook. Both these datasets were in the CSV format. Data pre-processing is done on both datasets to check the null values, outliers, and normalization of the data. Datasets have been divided into train and test datasets. The Qualitative dataset is scaled down to 3 to match the course attainment which is captured on the scale of 3 as elaborated in Table 6.9.

6.7.1 Characteristics of Feature Selection Algorithms

Since feature selection algorithms search for the space of feature subsets, they must take four fundamental issues affecting the nature of the search into consideration [249].

- Starting point: The direction of the search can be changed by choosing a starting point in the feature subset space. One way is to start with no features and add qualities one at a time. In this instance, it is claimed that the search is moving ahead through the domain. On the other hand, the search may start with all features and gradually reduce them. Further, the search traverses the search area backward. Another option is to start in the center and work your way outward from there.

- Search organization: A thorough investigation of the features except for a limited starting number of features, subspace is prohibitive. Possible subsets of the initial features exist.
- Evaluation strategy: The single biggest difference between feature selection techniques for machine learning is how feature subsets are evaluated. Unwanted features that are filtered out of the data before learning in one paradigm are known as the filter [250], which acts independently of any learning technique. These algorithms use heuristics to evaluate the value of feature subsets depending on the general qualities of the data.
- The induction algorithm should be taken into account when selecting features. This methodology, known as the wrapper, estimates the final accuracy of feature subsets using an induction process and a statistical re-sampling technique like cross-validation. The dataset in the proposed work has used cross-validation.
- Stopping criterion: When to stop scanning the space of feature subsets is up to the feature selector. If none of the options improves the quality of a current feature subset, the feature selector may stop adding or removing features, depending on the evaluation technique. Alternatively, the algorithm may continue to revise the feature subset till the merit does not decrease.

6.7.2 Correlation-based Feature Selection

Correlation between features can be used to pick features for classification tasks in machine learning, and this feature selection method can help typical machine learning algorithms. A feature is valuable if it is connected to or predicts the class; otherwise, it is meaningless [251] formalize this definition as

Definition 1: A feature T_i is said to be relevant if there exists some *ti* and *d* for which

$p(T_i = t_i) > 0$, such that

$$P(D = d/T_i = t_i) \neq p(D = d) \quad (1)$$

Empirical evidence from the feature selection literature shows that if one or more of the other features had a strong correlation with a feature, it is said to be redundant [252]. Various data features, including continuous, ordinal, nominal, and binary data features, are frequently used in supervised learning tasks.

6.7.3 Correlating Nominal Features

As a result of decision tree induction research, several strategies for measuring the quality of an attribute—that is, how predictive one characteristic is of another—have been created [253] [254]. When all the instances in a collection have the same value for a second attribute, the collection is said to be pure; when there are differences between the instances' values for the second attribute, it is said to be impure.

6.8 Attribute Discretization

Artificial neural networks and logistic regression models both demand the usage of high-quality data. The discretization of continuous variables is one technique for raising the quality of raw data. It can be a means to cope with outliers and significant findings, and it can be useful when some of the models' presumptions aren't met [255]. Discretization methods can be categorized as:

- Supervised versus. Unsupervised
- Global versus. Local
- Static versus. dynamic

When, discretizing features, the supervised method makes use of the class label. The difference between global and local methods relies on when discretization is performed. Local methods discretize during the induction process and global methods discretize features before induction. Different discretization for certain local parts of the instance space may be produced by local approaches. Some discretization techniques call for a parameter that specifies how many intervals at most should be used to divide a feature. After performing a discretization pass on the data for each feature, static approaches compute the value of each feature independently of the others. On the other hand, Dynamic approaches simultaneously search the space of potential values for all features. Interdependencies in feature discretization can then be represented in this way.

6.9 Validation of threshold

Machine learning paradigms have different categories depending on the dataset and how an algorithm is trained. Machine learning is further divided into various types such as supervised learning and unsupervised learning, reinforcement learning, etc. depending upon the type of data. Ensemble learning and artificial neural networks also have a significant role in the machine learning paradigm. Existing algorithms such as linear regression, random forest, decision tree, SVM, etc. are applied and accuracy can be measured by using R-square, MSE, RMSE, MAE, etc. These evaluation measures help to identify whether the model is the best fit or not [4][5][256][257][258][259].

6.9.1 Variation in the Level of Attributes

Overall attainment is attained using a three-level threshold: 1 - low, 2 - medium, and 3 - high. Levels 3, 2, and 1 range from 70% and above, 60% -69%, and 51-59% of students score more than the set target marks. Level 0 is less than and equal to 50% of students scoring more than set target marks.

6.9.2 Graphical representation of threshold value for a particular course code

The threshold for the proposed model is derived using the K-means clustering algorithm under unsupervised learning in machine learning. K in the K-mean clustering is decided by using the elbow method. K lies where a huge reduction in variation is found and there are no changes found in the graph after that. The size of the dataset used here is large, therefore k-means clustering is working well.

The below figure 6. 5 shows the results of cluster 1, which has counted on the y-axis nd overall attainment on the x-axis. In this cluster total number of entries found was 35 and out of that 18 entries show the threshold value as 3.

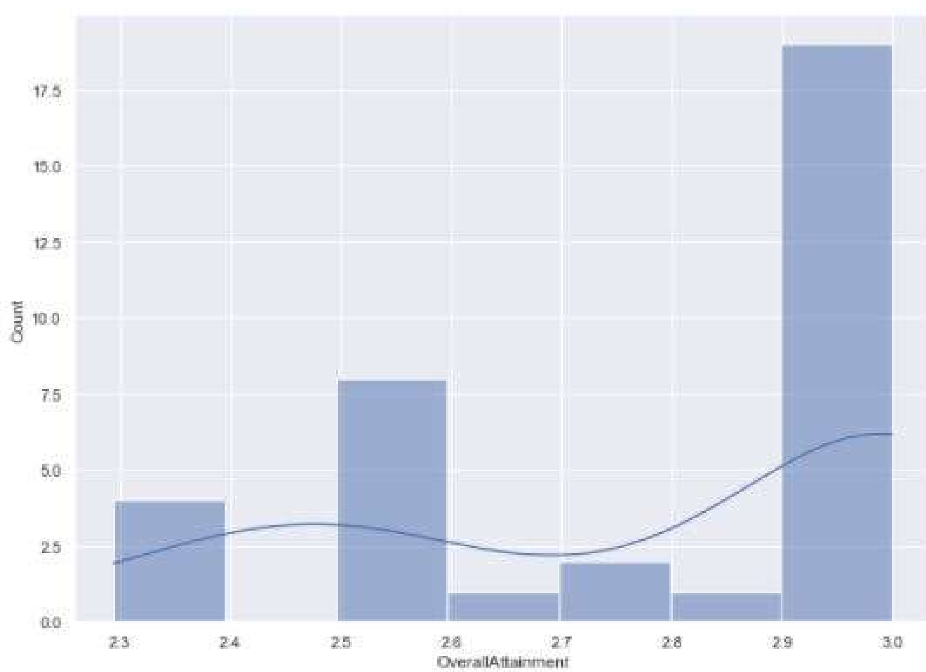

Figure 6. 5 A threshold in cluster 1

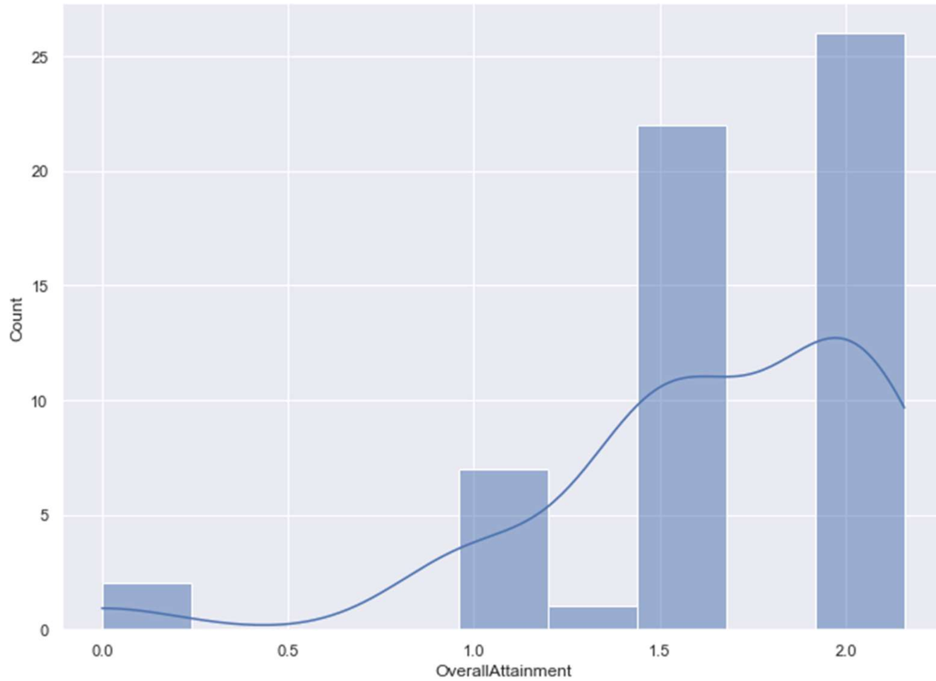

Figure 6. 6 A threshold in cluster 2

Figure 6. 6 depicted cluster 2, that have several entries i.e. 58, found using machine learning, and more than 25 values show the threshold value as 2. Therefore, after comparing both the clusters along with the threshold value it has been found and hence proved that the threshold value chosen as 2 is correct.

6.10 Learning Algorithms

Concept descriptions relate to the knowledge or model derived by the learning algorithm from the data. Knowledge may be represented differently by each algorithm.

6.10.1 Linear Regression

In the proposed work a linear model is used where academic emotions are used as input variables (x) and overall attainment is used as output variable(y). The relationship between these variables gives a solid base to draw the inferences from the proposed work i.e. academic emotions can be used to improve the overall attainment of the students. The major advantage of linear regression models is linearity: It makes estimating easier, and more importantly, the understanding of these linear equations at the modular level is simple. In a linear equation, a line is represented as follows

$$y = m * x + c \tag{2}$$

Where, y = dependent variable, x = independent variable, m = slope, and c = intercept.

In machine learning, the equation is written as

$$y(x) = v_0 + v_1 \mathrm{x} * \varepsilon \tag{3}$$

Where v's are the parameters of the model, x is the input, and y is the target variable. v0 = intercept of the line, v1 = linear regression coefficient and ε = random error.

6.10.2 Random Forest

The random forest algorithm offers a better level of accuracy in result prediction.

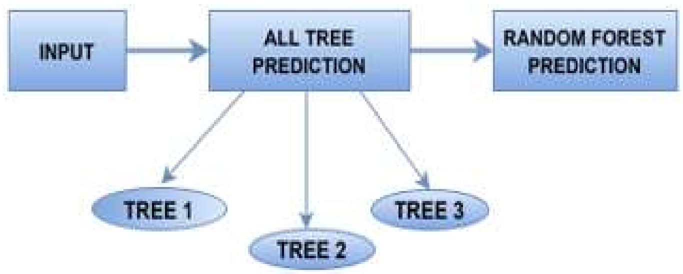

Figure 6. 7 Random Forest

It is a meta-estimator that uses averaging to reduce overfitting and increase predicted accuracy by fitting several classifying decision trees to different subsamples of the dataset. A Random Forest is an ensemble approach that can do both regression and classification problems by combining several decision trees using a technique known as Bootstrap Aggregation, or bagging. The Random Forest approach includes training each decision tree on a distinct data sample, including replacement sampling.

6.10.3 Decision Tree

The decision rules are built around if-then-else statements. The rules become more complex as the tree grows deeper, and the model matches the data better. It is easy to infer, understand, and visualize decision trees. Moreover, it is easy to understand the output of the decision tree. With replacement sampling, the Random Forest approach includes training each decision tree on a separate data sample. Large datasets can be handled effectively in comparison to the decision tree method. Decision tree algorithms [216] training data can over fit sometimes which results in large trees. In many instances, eliminating duplicate and superfluous data can result in smaller trees. Typically, decision tree induction only evaluates how predictive the class's attributes are. The feature-class correlations complement this. The general inductive bias of decision tree learners favors smaller trees over bigger ones. The bias in the attribute quality measure used to select which attributes to test at the tree's nodes can affect both the tree's size and how well it generalizes to new instances.

6.10.4 Ridge Regression

Ridge regression stands for the ridge regression cross-validation technique. Ridge Regression is a particular type of regression that is typically applied to multi-collinearity datasets. The proposed work has five independent variables and they are highly correlated with one another.

6.10.5 Gradient Boosting

In machine learning, "boosting" is a technique for fusing several simple models into a single composite model. The fact that adding basic models one at a time while maintaining the model's existing trees untouched boosts its reputation as an additive model. The ultimate, full model gets stronger as we merge more and more simple models. Since the algorithm employs gradient descent to minimize the loss, the term "gradient" in "gradient boosting" derives from this. Regression is used to compute the difference between the current anticipated and known correct target value. This fluctuation is referred to as residual.

6.10.6 K means clustering

K mean clustering is used, where distance (d) is computed between data points and the new centroid. If current d is less than the previous distance then the data point remains in the initial cluster otherwise it is transferred to the other cluster. K means++ the algorithm works in the background to find the centroid of the cluster. To choose the right number of clusters within a cluster sum of squares (WCSS) is used. The number of clusters identified in the given dataset is 2 and after applying K means clustering threshold value is found to be 2.

$$WCSS = \sum_{p_i \text{ in cluster } 1} Distance(P_1C_1)^2 + \sum_{p_i \text{ in cluster } 2} Distance(P_2C_2)^2 \quad (4)$$

Here P stands for the point in the cluster and C stands for the centroid of the cluster.

6.11 Block diagram of work done by using machine learning process

Figure 6. 8 explains the step-by-step machine learning process to handle the dataset and apply the technique to get results from the proposed model. The dataset is validated in the ratio of 80:20. This ratio can be divided into 90% for training and 10% for testing. Preprocessing of the data was done before the train-test split.

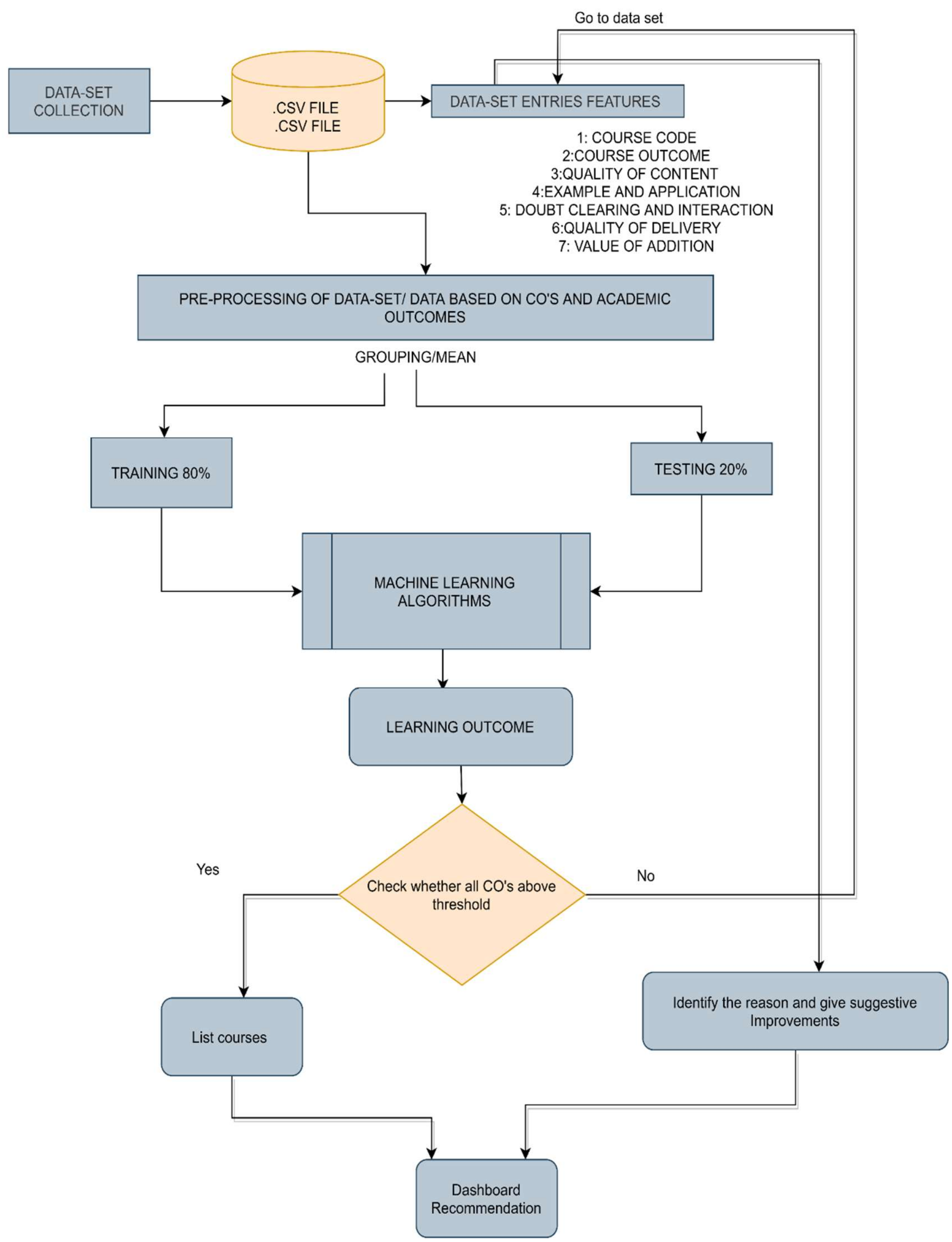

Figure 6. 8 Block diagram of Machine Learning used in research

6.12 Performance Evaluation

A key component of machine learning is assessing how well learning algorithms function. It is crucial to compare competing algorithms, but it is frequently also a crucial component of the learning algorithm. The most typical performance evaluation criterion is an estimate of classification or regression accuracy on fresh examples, while alternatives based on information theory have been proposed [260]. Because the examples in the test set have not been used to generate concept descriptions, measuring accuracy on a test set of examples is superior to using the training set. A typically optimistically biased estimate will be obtained when accuracy is measured using the training set, particularly If the training data is overfitted by the learning algorithm. For each partition, a learning algorithm is tested and trained, and accuracy results are averaged. This offers a more trustworthy assessment of an algorithm's real accuracy. There are a few popular resampling techniques: fold cross-validation and random subsampling. Random subsampling divides the data into distinct training and test sets at random. Each partition's average accuracy is utilized. For K-fold cross-validation, the data is randomly partitioned into roughly equal-sized, mutually exclusive groups. Every time a learning algorithm is tested, it is trained using the remaining K-folds and tested on one of the K-folds. The overall number of accurate classifications divided by the total number of examples in the data represents the cross-validation estimate of accuracy.

6.12.1 Results of Training and Testing Datasets

The dataset is trained on the ratio where. 80% data is used for training and 20% of the data is used for testing. Machine Learning algorithms like Linear regression, SVR, XGBRegressor, KNeighboursRegressor, Decision tree, and Ridge CV have been used for Training. R Square, MSE, RMSE, and AMSE have been calculated and depicted in Table 6. 10. R Square of the proposed intelligent mechanism is 0.720 on the training dataset.

Table 6. 8 Training Data Results

	LR	SVR	XGB Regressor	KNeighbors Regressor	DecisionTree Regressor	Random Forest Regressor	Ridge Regression	Proposed Intelligent Mechanism
R Square	0.654	0.676	0.7080	0.657	0.683	0.699	0.708	0.720
RMSE	0.079	0.076	0.0728	0.078	0.075	0.073	0.072	0.071
MSE	0.006	0.005	0.0053	0.006	0.005	0.005	0.005	0.005
AMSE	0.063	0.061	0.0583	0.063	0.060	0.059	0.058	0.056

Results of the testing datasets are depicted in Table 6. 11 and the R Square of the proposed intelligent mechanism is 0.668.

Table 6. 9 Testing Data Results

	LR	SVR	XGB Regressor	KNeighbors Regressor	DecisionTree Regressor	Random Forest Regressor	Ridge Regression	Proposed Intelligent Mechanism
R Square	0.655	0.643	0.648	0.591	0.642	0.649	0.655	0.668
RMSE	0.074	0.076	0.075	0.081	0.076	0.075	0.075	0.070
MSE	0.005	0.005	0.005	0.006	0.005	0.005	0.005	0.004
AMSE	0.059	0.076	0.060	0.011	0.049	0.005	0.016	0.014

6.12.2 Evaluation of existing machine learning models based on Training and Testing R square to finalize the proposed intelligent mechanism approach

Modeling the data and predicting the outcome is one of the key jobs in machine learning. The academic emotion TERE dataset initially had nineteen features and the CO attainment dataset has three features. Feature selection is done on both datasets and grouping of data is performed based on common variables in both datasets i.e. course code and COs. Feature scaling is done on the academic emotion dataset and scaled down to 3.

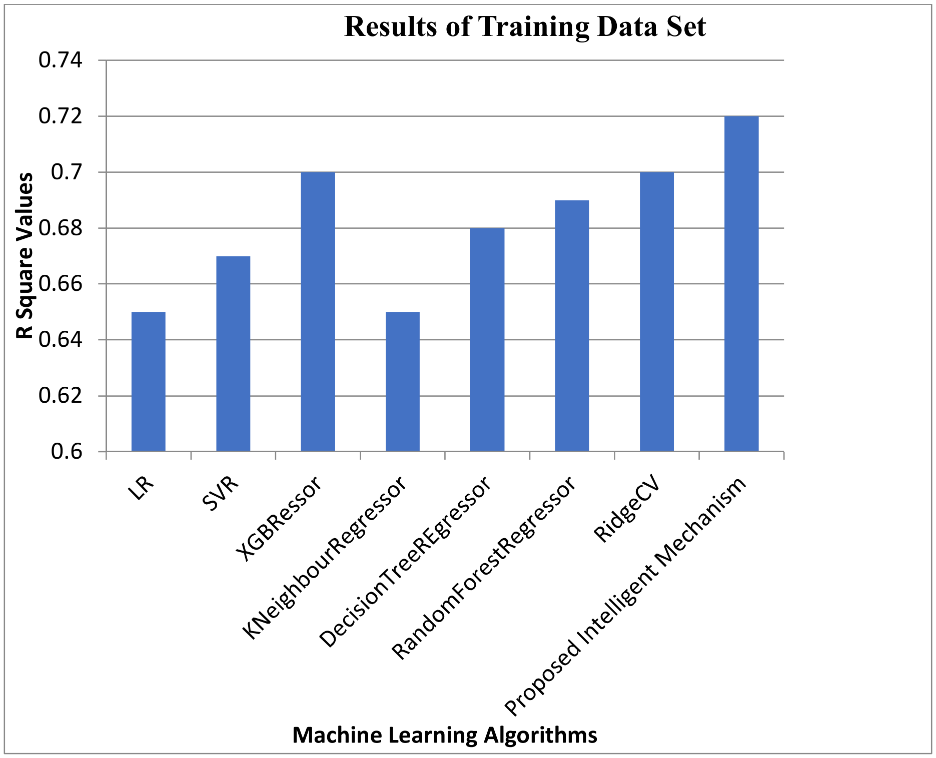

Figure 6. 9 Results of R-square on training dataset

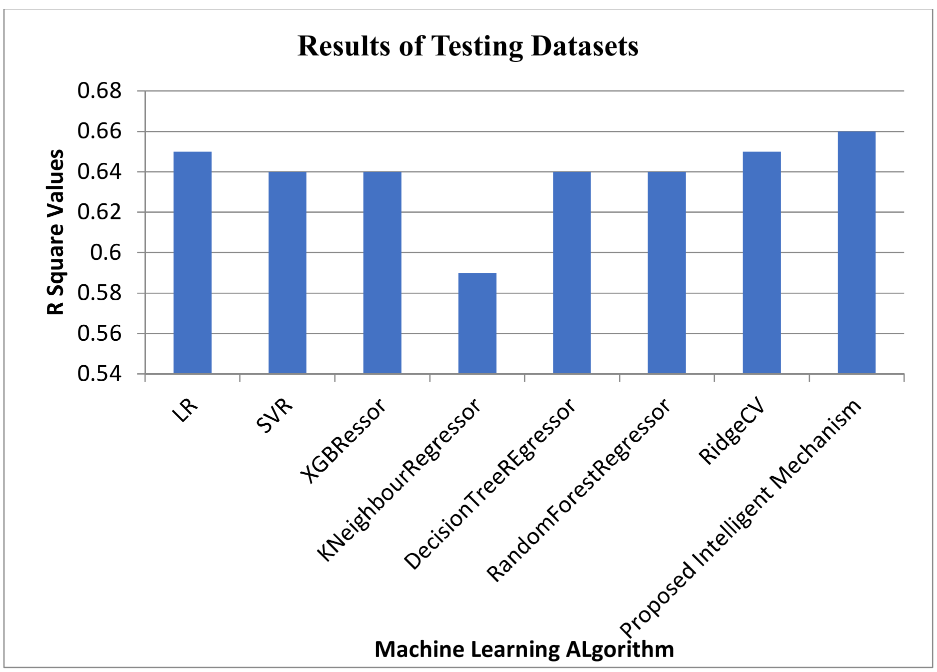

Figure 6. 10 Results of R-square on testing dataset

There are so many algorithms that come under regression that can be applied to given data and it's difficult to choose one for the prediction of the data. For the proposed work comparison of various existing models has been done. Therefore, by using the sklearn library, the Score and Mean square error of various machine learning algorithms have been assessed and the results are displayed in Figure 6. 9. An algorithm having a score greater than or equal to 0.7 means performing well. The mean square value ranges from zero to one, any algorithm having a mean square value of 0 is the best algorithm. It is clear from Figure 6. 10 that the proposed intelligent mechanism is performing best among the all algorithms applied to the validation dataset. The formula for MSE is as follows.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y - y_i)^2 \tag{4}$$

Where y = observed value, y_i= corresponding predicted value, and n = number of observations.

Firstly, the scoring method is used to import the train_test_split of the given dataset from sklearn.model_selection to split matrices into random train test subsets. Data is divided into features(x) and labels(y). For training fitting the model data frame is divided into x_train, x_test, y_train, and y_test. X_train and y_train sets. The coefficient of determination is used for score computation. The score method is written as follows.

$$Score = (x\_test, y\_test) \tag{5}$$

Here, x_test and y_test sets are used for testing the model if it’s predicting the right outputs.

6.12.3 Heat map to assess the multicollinearity among the independent variables in ridgeCV algorithm

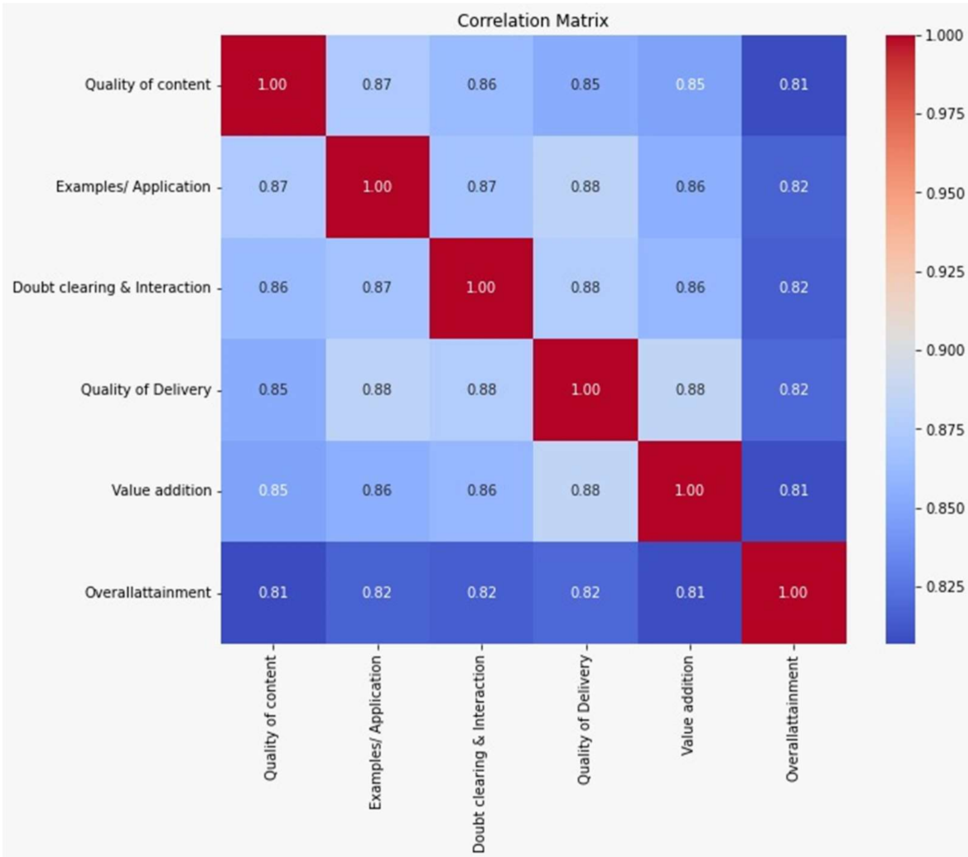

Figure 6. 11 Heat Map to check multi-collinearity

Figure 6. 11 shows that there is a high correlation among the academic emotions. The correlation between the quality of content and example and application is 0.87, the quality of content and doubt clearing & interaction is 0.86, the quality of content and quality of delivery is 0.85 and the Correlation between quality of content and value addition is 085. The results of the heat map show that independent variables are highly correlated with each other i.e. collinearity is found amongst the independent features. Therefore, the RidgeCV algorithm was found suitable to be used in the proposed model.

6.13 Proposed Intelligent mechanism

In the proposed model, initially, the academic emotion (TERE) dataset and the CO attainment dataset are fed together. On both datasets, feature selection is done. Grouping of data is performed based on common variables in both datasets i.e. course code and COs. After that feature scaling is performed on the academic emotion dataset.

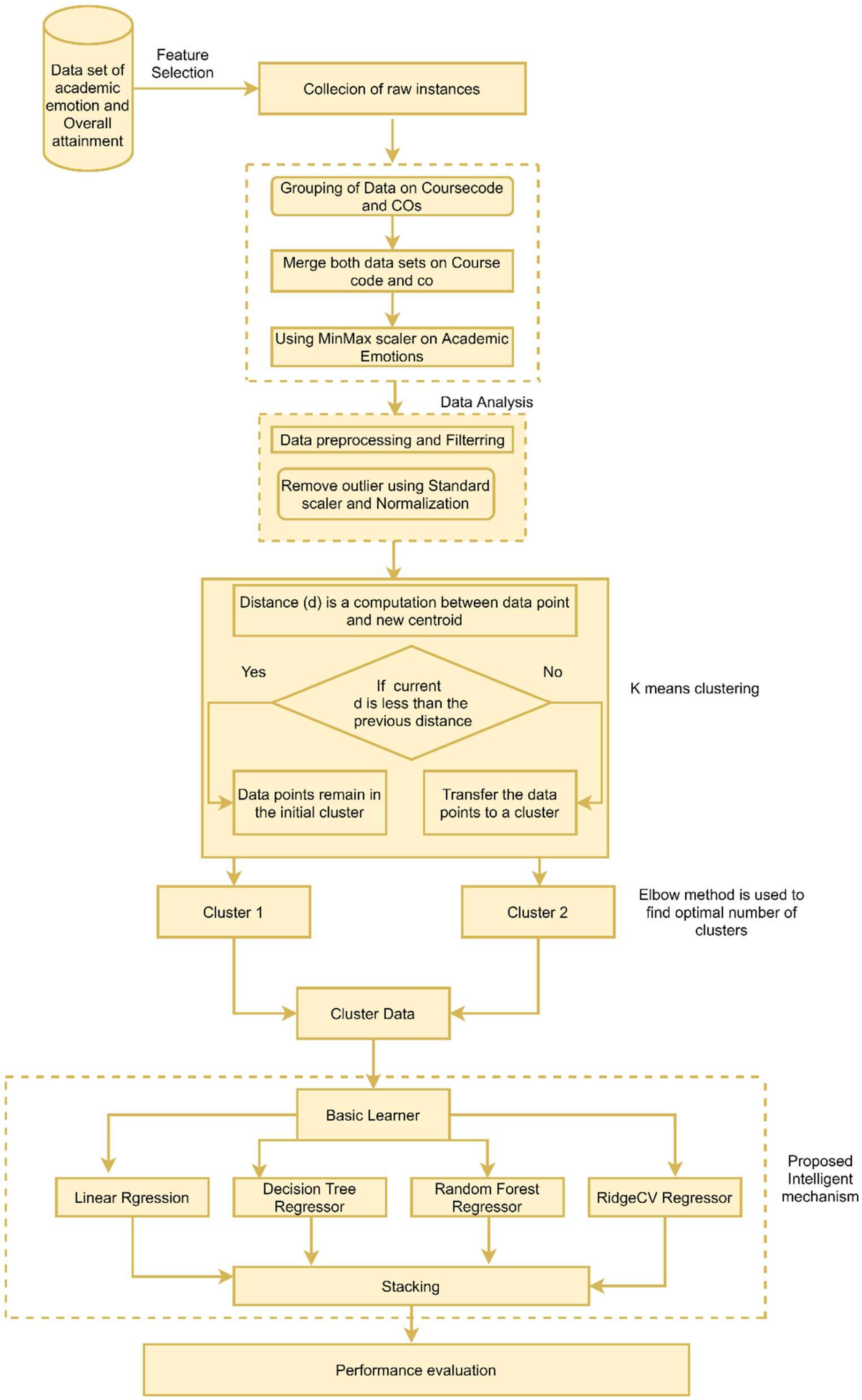

Figure 6. 12 Proposed intelligent mechanism

In Figure 6. 12, after collecting the datasets feature selection and scaling are performed after grouping and merging both datasets. Preprocessing of data is done to find, handle outliers, and normalize the dataset. The elbow method is used to find the prominent number of clusters in K means.

6.14 Results for primary suggestions

Results and suggestions on various courses have been discussed in this section. Firstly, the threshold value of a particular course has been identified then the proposed model derives the primary suggestions corresponding to the academic emotions. Finally, a graphical representation of the academic emotion with the least value has been highlighted.

6.14.1 Primary Suggestions parameter wise

Primary suggestions show the only one academic emotion in which the students are not satisfied. It reflects CO-wise course attainment & academic emotions for a particular course code. It shows the machine-learning implementation of the proposed dataset.

Table 6. 10 Threshold identification of Course-code CSE202.

CO's	Quality of Content	Example/ Applications	Doubt clearing and interaction	Quality of delivery	Value addition	Course Code	Course Attainment
CO1	2.72	2.66	2.64	2.6	2.7	CSE202	1.8
CO2	2.43	2.47	2.36	2.3	2.4	CSE202	3.0
CO3	2.64	1.06	2.60	2.5	2.6	CSE202	1.7
CO4	2.70	2.63	2.60	2.6	2.6	CSE202	2.0
CO5	2.59	2.64	2.61	2.6	2.5	CSE202	2.9

It reflects CO-wise course attainment & academic emotions for a particular course code. It shows the machine-learning implementation of the proposed dataset.

6.14.2 Primary Suggestions for improvement

In this section, discussions about the primary suggestions and attainment for multiple courses have been discussed. Results based on primary suggestions are shown in tabular form and graphically.

```
Doubt clearing & Interaction    2.64878
CO's                                CO1
Course                          CSE 202
Name: 0, dtype: object

Examples/ Application    1.06154
CO's                         CO3
Course                   CSE 202
Name: 2, dtype: object
```

Figure 6. 13 Ratings of academic emotions corresponding to CO having less threshold value in a particular course.

In Figure 6. 13 Suggestions for improvement have been given. In this particular case in a course, CSE202, CO1 was below a threshold value. So, all five parameters of academic emotions were seen corresponding to the CO1 by the proposed model, and the average of each parameter was calculated. From there it has been suggested that doubt clearing and interaction may need improvements to improve CO1 as this parameter had the least average values corresponding to CO1. In CO3, improvement in the examples and applications has been suggested.

Two COs out of five were below the threshold i.e. CO1 and CO3 in the course code CSE 202. The following graphs depicted and highlighted the academic emotion with the least value i.e. quality of content, example and application, doubt clearing and interaction, quality of delivery, and value addition in red color.

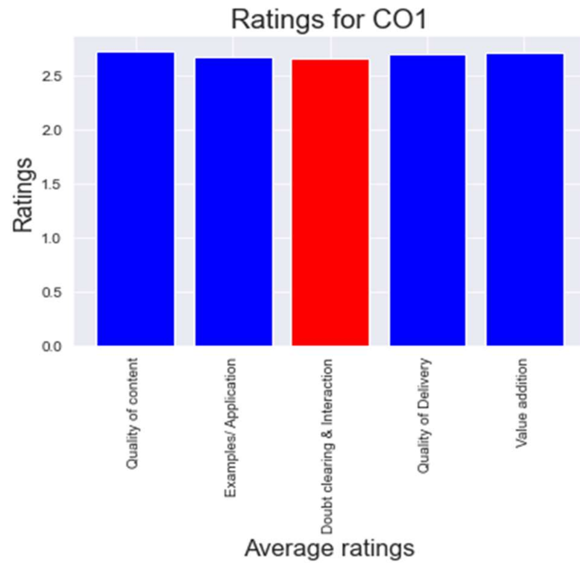

Figure 6. 14 Final threshold of CO1

In Figure 6. 14, the x-axis shows five parameters of academic emotions and the y-axis shows ratings from 0 to 3. In CO1, doubt clearing and interaction are highlighted with red color as it has a minimum average rating i.e. 2.64, and improvement is suggested in the same.

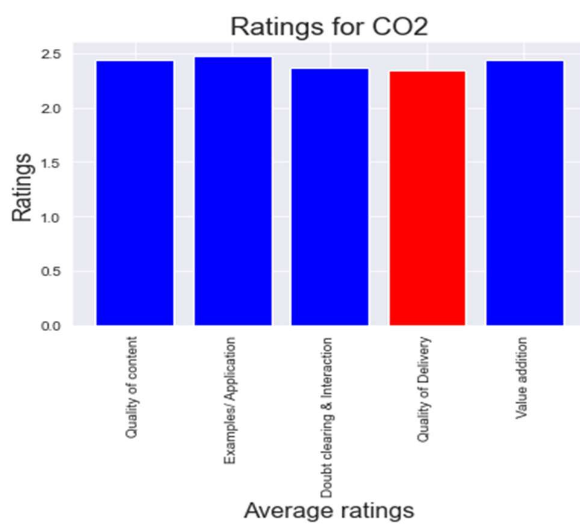

Figure 6. 15 Final threshold of CO2

In Figure 6. 15, the x-axis shows five parameters of academic emotions, and the y-axis shows ratings from 0 to 3. In CO2, the quality of delivery is highlighted with red color as it has a minimum average rating. However, it is not suggested for improvement because CO2 has a value above the threshold.

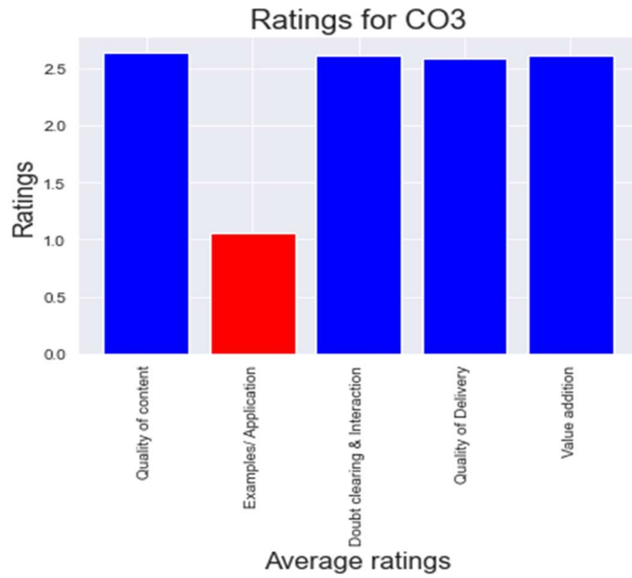

Figure 6. 16 Final threshold of CO3

In Figure 6. 16 x-axis shows five parameters of academic emotions and the y-axis shows ratings from 0 to 3. In CO3, examples, and applications are highlighted with red color as it has a minimum average rating i.e. 1.06, and improvement is suggested in the same.

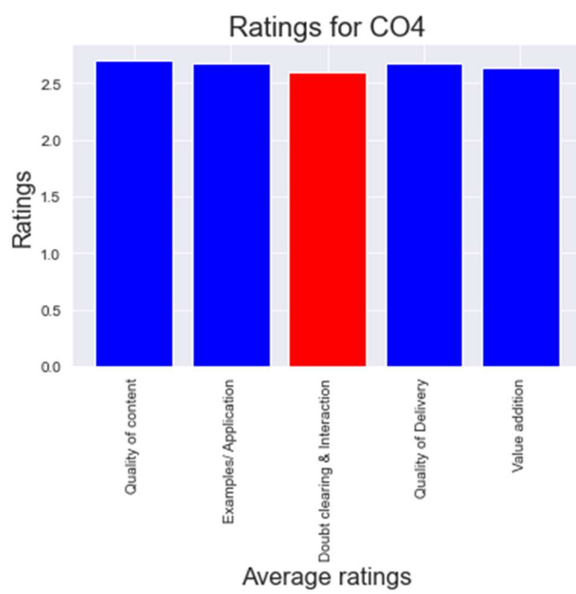

Figure 6. 17 Final threshold of CO4

In Figure 6. 17 x-axis shows five parameters of academic emotions and the y-axis shows ratings from 0 to 3. In CO4, doubt clearing and interaction are highlighted with red color as it has a minimum average rating but it is not suggested for improvement because CO4 has a value above the threshold.

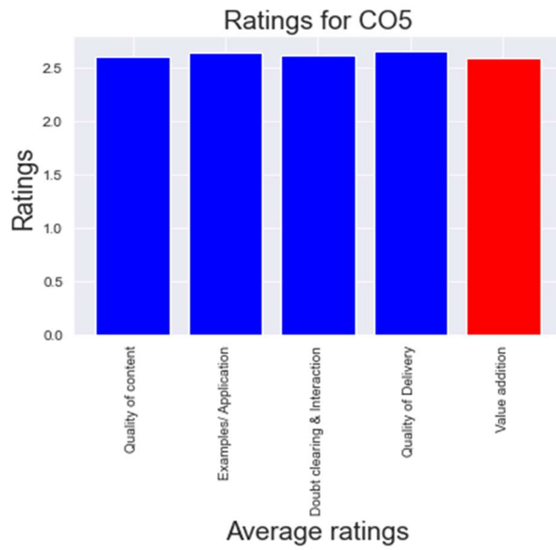

Figure 6. 18 Final threshold of CO5

In Figure 6. 18 x-axis shows five parameters of academic emotions and the y-axis shows ratings from 0 to 3. In CO5, value addition is highlighted with red color as it has a minimum average rating but it is not suggested for improvement because CO5 has a value above the threshold.

6.14.3 Learning outcome attained for multiple courses

The proposed model is generalized. Overall attainment of multiple course codes concerning COs is retrieved and suggestions for improvement from the parameters of academic emotions are given.

Table 6. 11 Course Outcomes less than Threshold in Multiple courses

Course Code	CO's	Academic Emotions & Rating
CSE38D	CO1	Examples and applications→2.29
CSE38D	CO3	Value addition→2.83
CSE42D	CO1	Doubt clearing and Interaction→2.11
CSE42D	CO4	Examples and Applications→1.54
CSE42D	CO6	Value addition →2.00

Course Code	CO's	Academic Emotions & Rating
CSE50D	CO1	Quality of content→2.49
CSE50D	CO3	Quality of content→2.16
CSE50D	CO6	Doubt clearing and Interaction→1.73
MEC82D	CO2	Quality of content→2.13
MEC82D	CO2	Examples and Applications→2.35
MEC82D	CO3	Examples and Applications→2.68

Table 6. 13 course codes CSE38D, CO1, and CO3 had ratings less than a threshold value, and improvements were suggested in the examples & application, and value addition. Similarly, in courses, CSE42D, CSE50D, and MEC82D, CO below a threshold is depicted in Table 6. 13. For the courses, CSE38 and CSE42D graphical representations with suggestive improvements are depicted in Figures 6-20 and 6-21.

6.14.4 Courses with suggestive improvements

Courses with suggestive improvements are identified and represented graphically.

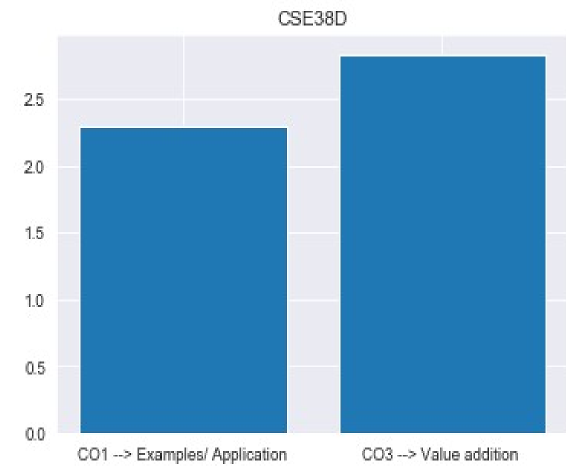

Figure 6. 19 Courses with suggestions in CSE38D.

Figure 6. 19 depicted suggestions for the course CSE38D which are in Example and application corresponding to CO1 and value addition corresponding to CO3.

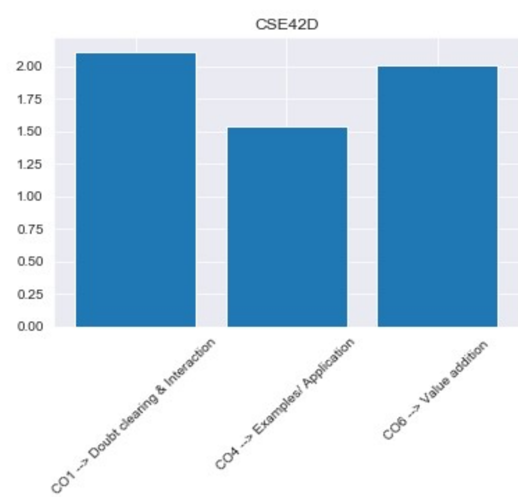

Figure 6. 20 Courses with suggestions in CSE42D.

Figure 6. 20 depicted suggestions for the course CSE42D which are in different academic emotions corresponding to various Cos.

6.15.5 Course code with Attained Learning outcome

Eventually, there is the possibility that some courses may achieve overall attainment in the entire COs in their respective courses. Therefore, table 6. 14 shows the list of courses with learning outcomes attained.

Table 6. 12 Courses with learning outcomes attained

CO Attained above Threshold
CSE32D
MEC42D
MEC84D

In Table 6. 14, the courses depicted have attained learning outcomes. These are the list of courses that have COs above the threshold. The courses CSE202, CSE32D, MEC42D, etc. have attained the course outcomes in all CO.

6.15 Results and discussions for primary and secondary Suggestions

In a Conventional system, mostly quantitative approaches were used to check the learning outcomes of the students but in the modern system, it is required to give qualitative data to show the compatibility of both approaches. In the present work, both quantitative and qualitative approaches are used to measure learning outcomes. For the Quantitative approach, the CO attainment measure is used, and on the other hand, for the qualitative approach, academic emotions are used.

6.15.1 Primary and secondary suggestions after checking threshold value

As per the proposed model CO attainment was checked whether it is above the threshold or not. If CO attainment is above the threshold then a list of courses will be displayed as satisfactory courses otherwise, reasons will be identified based on academic emotions and displayed as primary suggestions for the improvement of the overall attainment. To identify the least-scored academic emotions, it is necessary to find out the threshold value first. The following Table 6. 15, shows the CO's values below the threshold (i.e., using K-means clustering).

Table 6. 13 Threshold values CO-wise

Sr. No	Course Code	CO	Quality of Content	Examples and Application	Doubt clearing and interaction	Quality of delivery	Value addition	Overall Attainment
1	CHE22D	CO2	3.00	2.77	2.77	2.77	2.77	1.5
2	CHE22D	CO3	2.37	2.56	2.55	2.56	2.55	1.5
3	CHE22D	CO4	2.53	2.65	2.62	2.61	2.63	1.5

Table 6. 15 shows in the course code CSE22D CO2, CO3, and CO3 have overall attainment below the threshold i.e. 1.5. After getting CO below the threshold in a particular course code, suggestive primary and secondary improvements are identified and depicted in Table 6. 16 below.

Table 6. 14 Learning Outcomes less than Threshold in Multiple courses with primary and secondary suggestions

Course Code	CO	Primary Academic Emotions & Rating	Secondary Academic Emotions & Rating
CSE22D	CO2	Examples and Application→2.77	Doubt clearing & Interaction-→2.77
CSE22D	CO3	Quality of content→2.37	Doubt clearing & Interaction-→2.55
CSE22D	CO4	Quality of content→2.53	Quality of Delivery-→2.61

In Table 6. 16, it is depicted clearly that in course CSE22D CO2, CO3, and CO4 are below the threshold and it is also depicted in Table 6. 12. Further suggestions are listed to improve the learning outcomes of the students. In CO2 of the code CSE22D, the primary suggestion for improvement was given in the example and applications and a secondary suggestion was given in the doubt clearing & interaction. This model is a generalized model i.e. it can be implemented on multiple courses.

In Figure 6. 21, primary and secondary suggestions are given corresponding to the CO2 which has having overall attainment of 1.5.

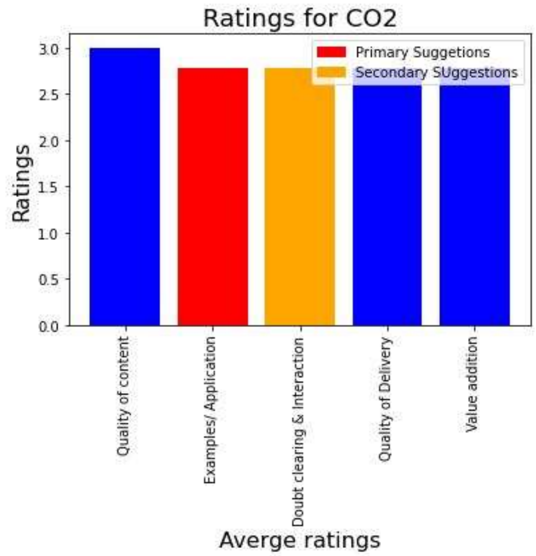

Figure 6. 21 Suggestions corresponding to CO2.

Figure 6. 21 shows academic emotions on the x-axis and ratings on the y-axis. The primary suggestion is given in examples and applications (represented by a red bar) and the second suggestion is depicted by doubt clearing and interaction (an orange bar).

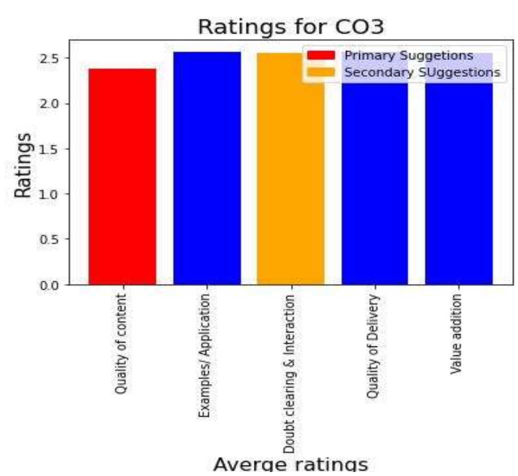

Figure 6. 22 Suggestions corresponding to CO3

In Figure 6. 22, suggestions are given corresponding to the CO3 which has overall attainment below the threshold. Figure 6. 22 shows academic emotions on the x-axis and ratings on the y-axis. The primary suggestion is given in quality of content and the second suggestion is given in doubt clearing and interaction in CO3.

In Figure 6. 23, suggestions are given corresponding to the CO4 which is overall attainment is not meeting the threshold.

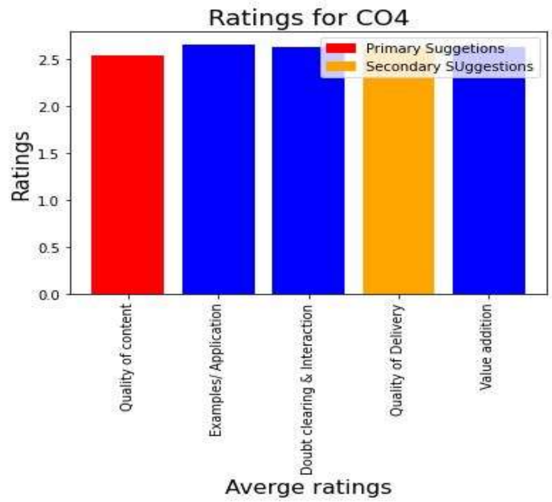

Figure 6. 23 Suggestions corresponding to CO4.

Figure 6. 23 shows academic emotions on the x-axis and ratings on the y-axis. The primary suggestion is given in quality of content and the second suggestion is given in quality of delivery in CO4 [243].

6.15.2 Courses with the suggestion

Further, the following figures 6. 24 and 6. 25 show the primary and secondary suggestions for a particular course after the identification of the CO values below the threshold. Figure 6. 25 shows the combined representation of the primary suggestions in course CSE22D.

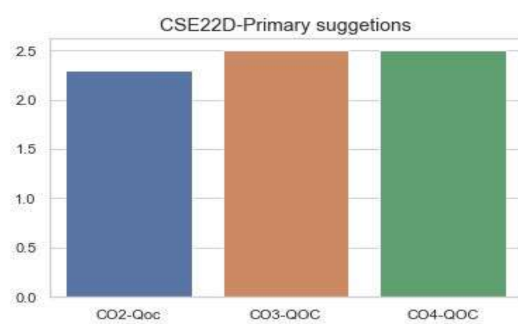

Figure 6. 24 Primary suggestive improvements.

The X-axis represents the COs with suggestive improvements and the y-axis represents ratings. Here QOC stands for the quality of content. The following figure shows the secondary suggestions for course CSE22D.

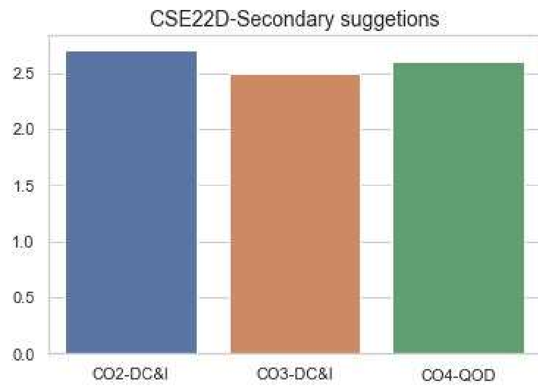

Figure 6. 25 Secondary suggestive improvements

The X-axis represents the COs with suggestive improvements and the y-axis represents ratings. Here DC&I stands for doubt clearing and interaction and QOD stands for the quality of delivery.

6.15.3 Courses with learning outcomes achieved

There are some courses in which overall attainment is achieved corresponding to COs.

Table 6. 15 List of Courses with learning outcomes attained.

Satisfactory Courses
CHE01D
CSE34D
ECE31D
ELE63D
MEC62D
MEC64D
MTH01D
PEL01D

In Table 6. 17 lists of courses are given that have CO attainment above the threshold, therefore no improvements are suggested in these courses.

6.15.4 Course wise academic emotions of each CO

The following figures depict the course-wise academic emotion of each CO. These figures aim to identify which CO attained the maximum rating in academic emotion parameters. One by one each parameter of academic emotions is taken corresponding to the COs.

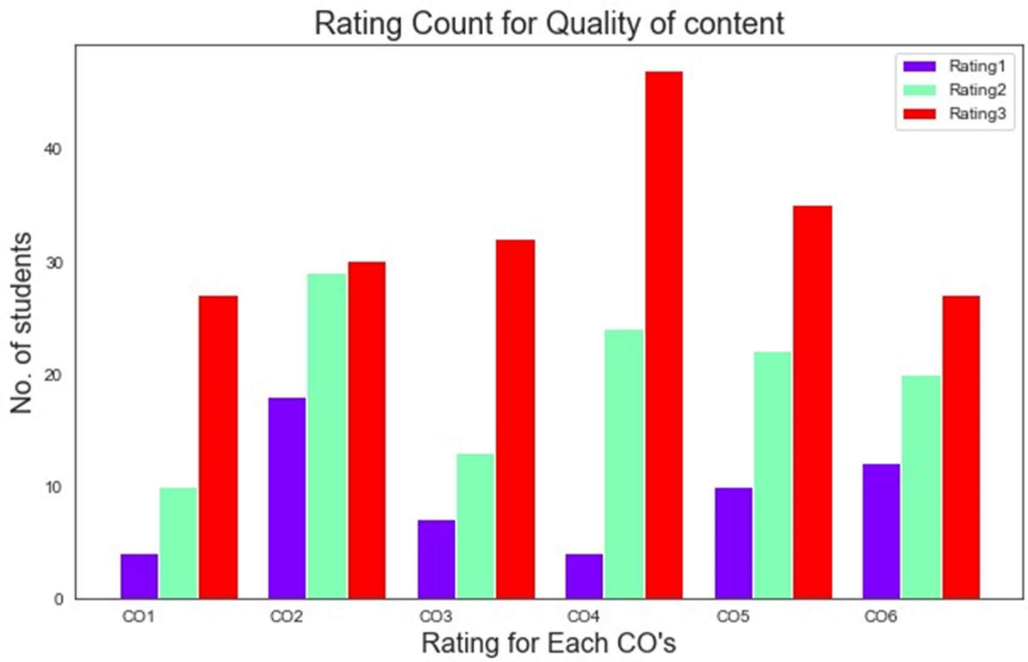

Figure 6. 26 Quality of content CO-wise.

In Figure 6. 26 x-axis shows the CO-wise rating and the y-axis number of students. This figure depicted students' ratings in different COs corresponding to the first academic emotion i.e. quality of content. Quality of content had the highest rating in CO4 i.e. most students were highly satisfied with the quality of content in CO4. In CO6 maximum number of students had given a minimum rating. Rating3 is the highest and rating1 is the lowest.

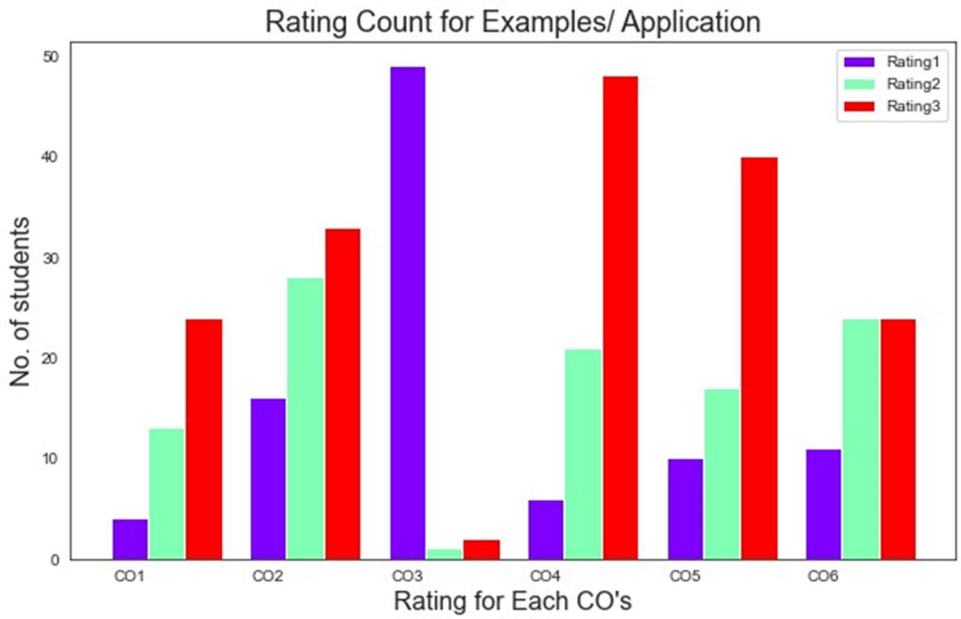

Figure 6. 27 Example and Applications CO wise

In Figure 6. 27, examples and applications had the highest rating in CO4 i.e. maximum students were highly satisfied with examples and applications in CO4. In CO3 maximum number of students had given a minimum rating.

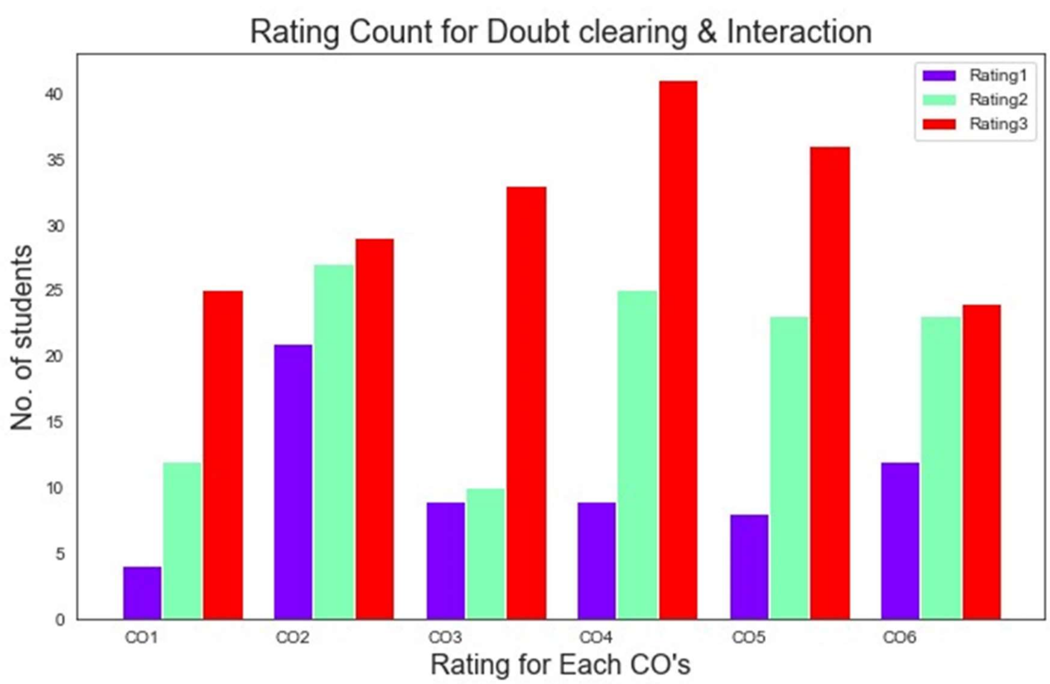

Figure 6. 28 Doubt clearing and interaction CO-wise.

In Figure 6. 28 doubt clearing and interaction had the highest rating in CO4 i.e. maximum students were highly satisfied in CO4. In CO1 maximum number of students had given a minimum rating in doubt clearing and interaction.

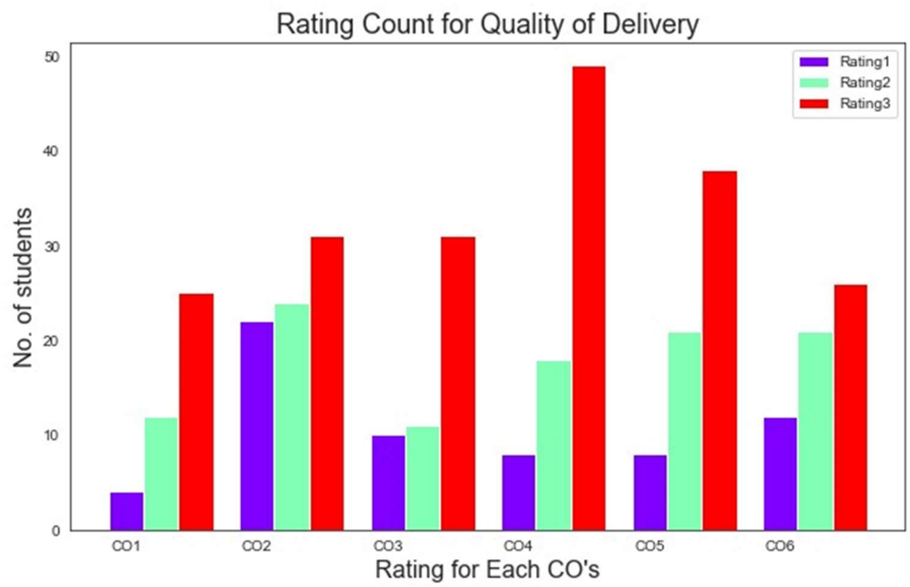

Figure 6. 29 Quality of delivery CO wise.

In Figure 6. 29 quality of delivery had the highest rating in CO4 i.e. maximum students were highly satisfied in CO4. In CO1 maximum number of students had given a minimum rating.

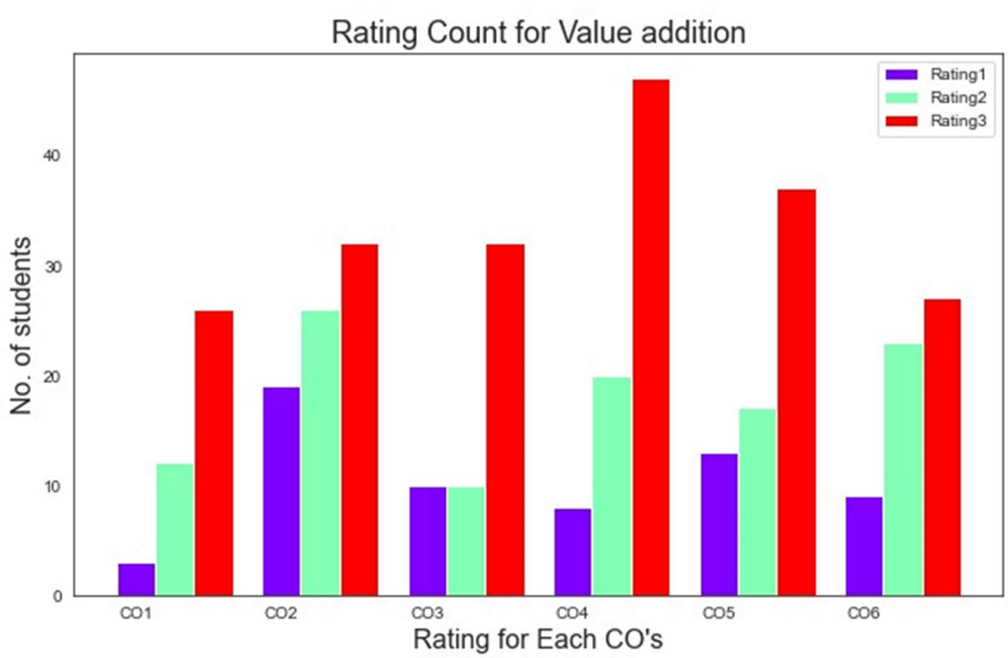

Figure 6. 30 Values addition CO wise

In Figure 6. 30 value addition had the highest rating in CO4 i.e. maximum students were highly satisfied in CO4. In CO1 maximum number of students had given a minimum rating. In CO3 the same number of students had given the rating 1 and 2. Overall it has been seen that students were highly satisfied with CO4.

According to research, making students aware of their emotions and motives can help them learn more effectively, and promoting self-regulation via technology can help them learn more effectively [115]. According to research, making learners aware of their emotions and motives can help them learn more effectively [116][117], and promoting self-regulation via technology can help them learn more effectively. The Recommender System assesses a student's learning productivity and enthusiasm for learning in real-time [251]. A novel model here captures the student's academic emotion in real-time which shows the actual feedback of the students and considers both aspects of the education i.e. qualitative and quantitative. It will help in improving students learning well on time.

6.16 Summary

It is seen that educational psychologists making great strides in understanding the central role of emotions in students' academic journey [3]. Therefore, the proposed model retrieves and depicts all the courses where the learning outcomes of the students were not achieved. An intelligent algorithm is also proposed using machine learning and a graphical representation is given using the matplotlib library in jupyter notebook.

6.17 Discussion

There are various existing studies related to learning, these studies are either related to the qualitative measure of learning or the quantitative measure of learning. A qualitative measure of learning includes parameters like self-regard or determination, stress tolerance, enjoyment, hope, confidence, enthusiasm, pride, anxiety, boredom, interest, irritation, nervousness, anger, quality of content, etc. Even in e-learning Enjoyment, boredom anxiety, etc. are practical implications for the emotional design of learning and developing a more complete theory [120], According to the findings, students who are enthusiastic about their studies are more likely to participate in academic procrastination [158]. Students' creativity, motivation, curiosity, performance, and social cohesiveness can all benefit from positive emotions [159].

Emotional intelligence and its aspects are statistically significant predictors of academic performance in students where intrapersonal mode is a positive and a negative predictor as well. With the support of distinct learning tools, the qualitative output of learning increased with time, and learners achieved considerable gains in the learning process [219]. Qualitative assessment methodologies and theoretical foundations derived from qualitative research may help to promote a more holistic picture of the student college experience, and in certain situations, give a more thorough insight than quantitative evaluation methods alone.

After going through a detailed literature survey, it has been identified that quantitative measures of learning outcomes consider parameters such as scores achieved, quizzes, tests, interactive videos, discussions, number of files viewed, questionnaires, effects of assessment on learning, fairness of assessment, conditions of assessment, the authenticity of assessment, oral presentation, interviews, etc.[224] . Quantitative learning measures are based on the scores achieved by the students in mid-term, end-term, assignments, etc. The previous studies either included the measure of learning outcomes or the measures of a qualitative measure of learning. The goal of this strategy is to ensure that the problem is thoroughly examined by gathering both quantitative and qualitative data [225]. In the proposed study both the qualitative and quantitative measures of learning are used. Here, qualitative measures (academic emotion) are captured using 5 parameters i.e. quality of content, example, and application, doubt clearing and interaction, quality of delivery, and value addition in real-time. A quantitative measure of learning is measured on scores achieved by the students in mid-term, end-term, and assignments. This novel model identifies the reason why translation in the teaching-learning process is not happening and the solution is also recommended. This model considers both sides of education and delineates the correlation of these measures for recommending the underperforming parameters. A qualitative measure of learning is supplemented with a quantitative measure of learning to improve the delivery based on academic emotion CO-wise. The threshold in the proposed model is validated as 2 by the KNN algorithm of machine learning. This is a generalized model in which multiple course COs below the threshold can be identified and the least rated academic emotion corresponding to that particular CO is identified for the improvement in delivery. This model enjoins the real-time reviews given by the students and their academic achievements. There are some courses in which all CO are above the threshold which shows learning outcomes are achieved. Therefore, in these courses, improvements are not suggested as it is not required.

6.18 Conclusion

The present scenarios, qualitative and quantitative measures of learning outcomes are treated separately and this research identifies it as a major gap. In this research, the academic emotions of the students were captured based on the unique framework TERE. A novel aggregation model is proposed to evaluate the learning outcomes and improvements are suggested by comprehending the qualitative reviews given by the students on the real-time and quantitative performance of the students. An intelligent model helps to evaluate the learning outcomes of the students at any time throughout the semester and modifications can be made to improve the learning of the students. This is a generalized model that checks the overall attainment of multiple courses at a time using machine learning. The proposed model worked on the micro-level i.e. academic emotions are captured lecture-wise along with COs. Eventually, the lecture-wise learning outcomes of the students are summed up to get the unit-wise learning outcomes and finally produce course-wise learning outcomes by adding up unit-wise learning outcomes. Here learning outcomes of the students were measured using CO attainment of the students instead of using direct mid-term and end-term marks of the students. In this study, qualitative measures worked as complementary means to the quantitative measure, and a novel model was used to collate academic emotions with learning outcomes. The model is unique and would pave new dimensions for unraveling truthful reasons for underperformance lecture-wise so that dynamic updates in the teaching-learning process can be done.

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

Students' learning outcome plays a crucial role in academics. It includes assessment, course learning outcomes, mapping, and qualitative and quantitative measures of learning. Learning outcomes are majorly divided into direct i.e. quantitative and indirect i.e. qualitative measures. In the present time, either of the two qualitative or quantitative aspects of student learning outcomes has been considered. The hour requires to enjoin both aspects of learning and filling the gap. Using student learning aspects individually does not reflect the true overall attainment of learners.

7.1 Conclusion

In academia, various mechanisms for assessing the learning outcomes have been practiced. These mechanisms have been studied thoroughly and comparative analysis has been made based on the evaluation mechanism given in Table 3. 2 of Chapter 3, and comparative analysis based on student's academic emotions is given in Table 3. 3 of Chapter 3 of. After the Literature review it has been identified that in the current scenario, either qualitative or qualitative aspects of student learning outcomes have been considered. Where quantitative measures are designed as per regularities bodies and qualitative measures consider the academic emotions of the students.

Therefore, after considering the literature review in the proposed work, a real-time framework (TERE) has been developed to capture the real-time academic emotions of the student. These emotions are captured on the five parameters i.e. Quality of content, Examples & Application, Doubt clearing & interaction, Quality of delivery, and Value Addition as soon as the lecture has been completed. The combination of these five parameters for capturing the academic emotions of the students has not been considered in the existing studies. A dataset has been generated using the TERE framework for the fall and spring sessions and it is a granted Indian copyright (copyright number SW-14125/2021) in the title of Teaching Effectiveness Rating Engine (TERE). Further comparative analysis based on qualitative parameters with existing parameters has been done in Table No. 4. 7 of Chapter 4. Similarly, comparative analysis based on Quantitative measures used in the proposed work has been done with existing parameters in Table No. 4. 8 of Chapter 4.

The Proposed work considers and enjoins both Qualitative and quantitative measures and an aggregation model has been proposed for summing up lecture-wise learning outcomes for evaluating unit-wise and course-wise learning outcomes on a real-time basis. An aggregation model is used to get real-time predictions about the student learning outcomes. Combining both qualitative and quantitative measures results in resolving the issues identified in the literature review and proposes a novel idea for measuring student learning outcomes.

An intelligent mechanism is proposed herein after comparing with existing models available in machine learning for a truthful assessment of the learning outcome of a course. The elbow method is used to find the prominent number of clusters in K means. A K-means algorithm has been used for the identification of the threshold and recommendations are provided for improvement in the learning outcomes. If any course's outcome is below the threshold then academic emotions corresponding to that CO have been checked and the least scoring of two academic emotions are recommended for improvement. In this way, qualitative measures supplement the quantitative measures of student learning outcomes. The main focus of this work is to provide recommendations about courses in which the learning outcomes of the students are not attained. The novelty of this work is that it combines both the quantitative measures and the qualitative emotions of the students. An aggregation model has been developed in a real-time based to retrieve the result. Real-time data has been collected from the TERE framework to capture the student academic emotions. Primary datasets have been used for the aggregation model and give suggestions to improve students' learning outcomes.

7.2 Findings

In the present work, a novel model has been proposed and examined. This work aims to improve evaluation mechanisms in the field of assessment of student learning outcomes. It aims to present a unique model to enhance the student's learning outcomes. Various existing machine learning algorithms have been applied to real-time primary datasets and an intelligent model gives the best results amongst other Machine learning algorithms. Following are the key findings of the proposed work

- Learning outcomes of the students are captured at micro to macro level and academic emotions are captured lecture-wise on a real-time basis.

- This model covers both sides of academics i.e. students and teachers. Students give feedback about a lecture and it can be concluded from data corresponding to each course code that academic emotion out of five parameters scored less.
- The same information can be shared with the teacher and improvements can be made in the upcoming semesters.
- With the help of feedback from the students, the overall attainment of a course code can be improved by giving a prominent focus on the CO or COs of a particular course code. Furthermore, least scoring two academic emotions recommended by the model can be improved in the upcoming time.
- Prediction results are seen based on the overall attainment and model evaluation. Inferences are drawn to improve the learning outcomes of the students by improving the parameters corresponding to their academic emotions. The R-square for the proposed model on the validation dataset was 0.668 %.

7.3 Future Work

The study in this thesis presents a robust combination of both qualitative and quantitative measures to assess student learning outcomes, with a particular emphasis on the effectiveness of the proposed intelligent mechanism. The mechanism has demonstrated superior results in various key metrics.

However, there is significant potential for further improvement in terms of sensitivity, F1 score, R-square, and accuracy. In addition to enhancing these performance indicators, future research can extend the applicability of the model beyond engineering courses to incorporate other disciplines. This extension would make the model more versatile and generalizable across diverse educational fields, broadening its impact.

From a societal perspective, this work holds great promise for enhancing the education system. It offers practical insights that can be leveraged to streamline the processes of Boards of Studies (BOS), potentially reducing their workload. This, in turn, could aid in curriculum design by providing a data-driven approach to shaping educational programs. Moreover, the model's ability to deliver real-time feedback can significantly contribute to improving student learning outcomes by enabling timely and effective pedagogical interventions.

Finally, this model has the potential to be expanded on a global scale, where its intelligent feedback mechanisms can benefit various educational systems worldwide. The implications of this research are vast, and its continued development will likely make it an invaluable tool for educators, curriculum designers, and policymakers alike.

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LIST OF PUBLICATIONS

- Pooja Rana[1]*, Lovi Raj Gupta[2], Mithilesh Kumar Dubey[3], Amit Thakur[4], "A model to combine qualitative and quantitative measures in education for better assessment of learning outcomes" in *Interactive Learning Environments*, 2023.
- Pooja Rana[1]*, Lovi Raj Gupta[2], Mithilesh Kumar Dubey[3]," A Review on Machine Learning approaches in the education sector with Real-Time Data" in *Journal of algebraic statistics*, 2022.
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- Pooja Rana[1]*, Lovi Raj Gupta[2], Mithilesh Kumar Dubey[3], Gulshan Kumar[4]" An ensemble learning approach to improve qualitative and quantitative measures of learning" has been communicated in the *International Journal of Modern Education and Computer Science (IJMECS),* 2024.