"ANALYSIS OF MACHINE LEARNING BASED TELEMEDICINE SYSTEM FOR REMOTE DISEASE DIAGNOSIS USING FOG COMPUTING AND INTERNET OF MEDICAL THINGS (IoMT)"

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Electronics and Communication Engineering

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Transforming Education Transforming India

LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

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DECLARATION

I, hereby declare that the presented work in the thesis entitled **"ANALYSIS OF MACHINE LEARNING BASED TELEMEDICINE SYSTEM FOR REMOTE DISEASE DIAGNOSIS USING FOG COMPUTING AND INTERNET OF MEDICAL THINGS (IoMT)"** in fulfillment of the degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision of **Dr. Manwinder Singh**, working as Professor, in the **School of Electronics and Electrical Engineering of Lovely Professional University, Punjab,** India.

In keeping with the general practice of reporting scientific observations, due acknowledgements have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **"ANALYSIS OF MACHINE LEARNING BASED TELEMEDICINE SYSTEM FOR REMOTE DISEASE DIAGNOSIS USING FOG COMPUTING AND INTERNET OF MEDICAL THINGS (IoMT)"** submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Electronics and Communication Engineering, is a research work carried out by **Ankush Kadu,** 41900774, is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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ABSTRACT

With the development and notoriety of artificial intelligence (AI) in various fields, medical concentrates have started to actualize their capacities to care for and interpret information through telemedicine. With the difficulties in the usage of telemedicine, it is required to enhance its abilities and improve its adaptability to resolve problems in telemedicine. The continuous improvement in technology that prepares for the extension of associations through the Internet, i.e., the Internet of Things (IoT), and the development of the ability to handle information have made more noteworthy prospects of advancing the worldwide health industry, particularly telemedicine. With due advantages, telemedicine and AI gave unlimited opportunities for improvement, and the literature of existing work has been reviewed in this paper. The recent development with this technology can be characterized into four: information analysis collaboration, intelligent assistance diagnosis, healthcare information technology, and patient monitoring.

WBANs (Wireless Body Area Networks) significantly automate. On the contrary, these systems create a large volume of sensed data, necessitating time-bounded services, dependability, data preparation, and effective communication technology. One of the acceptable choices to improve patient monitoring systems is the IOT with the notion of Fog computing. The massive surge in health-related digital information has changed machine learning algorithms, allowing them to produce more relevant information. Remote patient monitoring and recognizing threats to human health have become critical components of modern telemedicine. In this research work, epilepsy disease diagnosis is considered in telemedicine. Patients with epilepsy are more likely to die or have post-traumatic problems. As a result, early disease detection might be critical for a person's survival or for giving vital support. On the other hand, telemedicine data centers require scalable processing and storage resources to accommodate the expanding number of people being watched. Dedicated techniques are also necessary, allowing minimal data transmission of only the most interesting cases.

The main objectives of the proposed model are

1. To study and analyze existing telemedicine system for different wireless network technologies.

2. To develop Internet of Things (IoT) enabled Fog Computing based architecture of Telemedicine system for diseases diagnosis and to monitor remote health care services.

3. To develop and analyze machine learning-based fog computing for an efficient e-health care system.

4. To evaluate and compare the proposed method with existing methods regarding confusion matrix, receiver operating characteristics, latency, and energy consumption.

To justify the above objectives, this research work is mainly focused on the needs of epilepsy patient monitoring systems before proposing and implementing a hierarchical layer-based IoT architecture that incorporates WBANs, fog computing, and cloud services. In this proposed model, a novel epilepsy classification method presented based on health metrics that uses machine learning and fuzzy logic. In addition, the suggested is tested using an embedded system and an open-source prototyping platform.

Initially, the real-time health parameters from wearable sensors, respiratory rate, body temperature, air quality, SpO2, and heart rate of a person, are monitored, deliberated, and analyzed to assess the system's efficacy in various human activities. The values of each sensor parameter are observed for two sensor nodes connected to healthy people, and the distributions were statistically significant displayed on the Ubidots cloud services. As per anomaly found in sensor data as per the threshold assigned, an alert will be sent to the doctor or caretaker. The findings demonstrate that this architecture meets the stringent criteria of medical applications by delivering reliable communication.

Later, the suggested approach distinguishes new instances based on disease symptoms and regular health markers. To forecast and compute the severity of the discovered disease for each sign of illness, different coefficients were used. The proposed method involves using wearable sensors with additional sensors to capture more data on the patient to enable a better and more accurate diagnostic to evaluate the patient's state

while they are being observed. Using a combination of machine learning and fuzzy logic, the system can diagnose and treat epilepsy patients with more intelligence and precision. Different classifiers were used to classify the Epileptic Seizure dataset. Compared to other classifiers, the Random Forest classifier with Fuzzy Inference System outperformed. Sensitivity analysis was performed on several of these classifiers to see how well they performed in classifying the Epileptic Seizure dataset when some parameters were changed. After that, a dataset prediction was made using feature selection based on attribute variance.

The results are analyzed based on confusion matrix parameters, such as accuracy, sensitivity, specificity, f-score, positive and negative predictive value, false positive rate, and negative rate with receiver operating characteristic (ROC) with latency time required for training and testing of the model. Over 98% accuracy is achieved utilizing the same dataset to evaluate the effectiveness of ensemble machine learning algorithms and their processing needs. Our proposed method's results demonstrated that ML-FIS could be used to diagnose different disorders. Finally, the proposed model is compared with the state of art model, and it is much superior in all aspects. The suggested method controls sensor-based patient monitoring and demonstrate acceptable accuracy and savings compared to traditional methods. The study was tested on a subset of the population, where its superior precision and efficacy were quickly apparent. The recommended approach has been general thus far; however, it may be adapted to more pressing situations, such as those seen in operating rooms, critical care units, with infants, and with more complicated patients. The findings suggest that a machine learning–fuzzy logic system can effectively replace high-end, costly intelligent decision-making systems. Further, this research could help doctors, patients, medical practitioners, and other healthcare professionals detect diseases earlier and treat them more effectively.

Keywords: Epilepsy, Fuzzy Logic Inference System, Machine Learning, Telemedicine.

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High achievement always takes place in the framework of high expectations. It has been rightly said that every successful individual knows their achievement depends on a community of people working together. However, the satisfaction accompanying the successful completion of any task would be incomplete without the mention of the people who made it possible. The expectation was there, and I began with a determined resolve and put in sustained hard work.

This is to acknowledge with gratitude the guidance and ameliorating suggestions from my supervisor, Dr. Manwinder Singh, for the support and motivation throughout the thesis work. I am grateful to the School of Research Degree Programme (RDP) members for being in my entire research progress review panel and providing valuable suggestions during the period. I am indeed thankful to all anonymous reviewers of my research papers submitted to various International journals and International conferences, due to which I was able to improve upon the work contained herein. I am indebted to Honorable Chancellor, Worthy Pro-Chancellor, the Vice-Chancellor, and the successive Deans, LPU, for facilitating the administrative issues involved and encouraging me throughout. I express my heartfelt gratitude to the Head o of the School of Electronics and Electrical Engineering, and the Electronics and Electrical Engineering School staff for their cooperation and support. No thanks are enough to express my deepest gratitude and sincerest love to my parents, whose rock-solid faith in me kept me strong in all circumstances. I also thank my wife, Renuka, for her wholehearted support and patience. I would like to express my special gratitude and thanks to my doctor (expert guidance), Dr. Somesh Chaudhary (MBBS, TDD) for imparting knowledge and supervising this novel research work.

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Ankush Kadu

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Abbreviation

AdB	AdaBoost
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interfaces
AUC	Area Under the Curve
BPM	Beats per minute
CF	Cognitive Fog (CF)
CNN	Convolutional Neural Network (CNN)
DM	Design Methodology (DM)
ECG	Electrocardiography
EEG	Electroencephalogram
EHR	Electronic Health Record
EMG	Electromyography
EMLR	Ensemble Machine Learning Regression
FIS	Fuzzy Inference System
FLIS	Fuzzy Logic Inference System
FN	False Negative
FNR	False Negative Rate
FP	False Positive
FPR	False Positive Rate
HS	Health Score

HTTPS	Hypertext Transfer Protocol Secure
IDA	Intelligent Diabetic Assistant (IDA),
IDE	Integrated Development Environments
IDE	Integrated Development Environments
IFCATS	Internet of Things enabled Fog Computing-based architecture
IFCATS	Internet of Things enabled Fog Computing-based architecture
IoMT	Internet of Medical Things
IoT	Internet of Things
ML	Machine Learning
MQTT	Message Queue Telemetry Transport’s
NPV	Negative Predictive Value
PDR	Pedestrian Dead Reckoning (PDR)
PPM	Parts per million
PPV	Positive Predictive Value
PSO	Particle Swarm Optimization
RDF	Random Decision Forest
RF	Random Forest
ROC	Receiver operating characteristic
SDK	Software Development Kit
SVM	Support Vector Machine
TCP/IP	Transmission Control Protocol/Internet Protocol
TN	True Negative
TP	True Positive

TPR	True Positive Rate
UI	User interface
WSNs	Wireless Sensor Networks

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CHAPTER 1 INTRODUCTION

1.1 OVERVIEW AND BACKGROUND

Each person needs rapid diagnosis and treatment if they ever hope to keep their body healthy and strong. Today's fast-paced lifestyle brings on many diseases, the consumption of unhealthy food, and the prevalence of stressful jobs. The healthcare industry is currently giving IoT much thought. Typically, an Internet of Things (IoT) based framework is prepared for integrating various things and sensors over the internet, with each related gadget having a unique identity that permits them to impart trade information without human mediation. The utilization of freely available IDEs (Integrated Development Environments) and SDK programming has made the implementation of IoT in the healthcare sector significantly easier. This integration has led to groundbreaking advancements in the effectiveness, affordability, and accessibility of health monitoring frameworks.

IoT is a novel concept that promises to improve communication in the future. The IoT is a network of interconnected physical things that can exchange data and instructions with one another and similar devices and systems across a network infrastructure, somewhat unlike the Internet itself. Exceptional identification of each transporting object is achieved by its characteristics. By 2020, it is expected that there will be 50 billion IoT devices in use. Understanding Wireless Body Area Sensor Networks (WBASN) is crucial before using the concept of IoTs for remote health monitoring.

Low-force, reduced-size, wearable, and lightweight are only a few of the characteristics of the sensor hubs that make up a WBASN. Electroencephalogram (EEG), electromyography (EMG), electrocardiography (ECG), accelerometer, beat oximeter, spinner, temperature, and heart rate observation are all used in clinical settings. These sensor nodes are crucial, as they can constantly monitor things while having a small amount of storage space. Constantly monitoring physiological data, these wearable sensor hubs transmit it through RF signals to a facilitator hub before memory fills for pre-processing. Certain persistent diseases and persistent settings are typical for IoT-based medical care. Constant developments in data and correspondence innovation have prompted updating the applied sciences. The WBAN has expanded the range of medical applications by reducing the need for remote sensors and other electronic equipment. Healthcare costs have decreased, and treatment durations have decreased due to the increased possibilities made possible by technological advancements. WBANs are better capable of handling traffic from various types of organisations, are more innovative, smaller in size, and have a shorter battery life. The IoT is a cutting-edge development that links physical objects to digital networks. WBAN engineering in healthcare administrations can benefit from this method [1].

Figure 1.1 Telemedicine Approach using IoT [Source: Device Authority Ltd]

Some of the most promising growth areas for the next decade include the exchange and analysis of data, the IoT, wearables, cloud computing, and mechanical technology. In particular, telemedicine has better potential for improvement due to the ongoing development of technology that allows for the creation of relationships via the web and the development of the ability to handle information depicted in figure 1.1. With these considerations in mind, it is clear that the use of artificial intelligence (AI) plays a crucial role in the development and implementation of new ideas in response to the massive amounts of data used in medical care, the need for predictable accuracy in complex methodology, and the increasing demands in medical care administration. Computerised scheduling and communication of medical care needs and activities may increase clinic efficiency.

Mobile health care, or mHealth, complements eHealth's emphasis on adaptability. With distributed computing, health records collected from any location may be securely stored and easily accessed, greatly enhancing patient care quality. Distributed storage, which provides on-demand stockpiling services, allows the customer to avoid dealing with the goods and equipment on a local level. When stored on the cloud, a patient's medical history is safe from destruction. A patient's medical history may be uploaded to a cloud-based service provider and accessed by treating physicians. However, the information included in health records is extremely valuable and may be used for various malicious purposes [2].

1.2 Telemedicine System

1.2.1 Introduction

Telemedicine is being moved in through user-friendly electronic messaging, allowing for the performance of conversations, clinical evaluations, and coordinating activities amongst clinical experts. In several articles, telemedicine is described as an "open and consistently expanding science" that incorporates "new headways in innovation" and "reacts and adjusts to the altering wellness requirements and circumstances of social orders." In the medical profession, telemedicine's essential functions include lowering deferrals, cutting costs, and increasing accessibility. Prioritizing cost-effectiveness and gaining the acknowledgement of the healthcare network, in the last ten years, remote innovation has been used to sensors and applied to contextual analyses identified using electronic patient records and home observing. Teleradiology, which transmits computerised radiological pictures (for example, X-beam pictures) from one area to the next; telepathology, which shows digitalized obsessive results; teledermatology, which transmits clinical data concerning skin conditions, and telepsychiatry for mental assessments and also meet-ups, are the four fields that will primarily benefit from the types of assistance provided by utilising data and correspondence innovations (ICT).

Its reach and capabilities, however, may be expanded thanks to new data emerging from studies of artificial awareness and information. When done right, telemedicine can increase efficiency, boost profits, and better allocate resources [3].

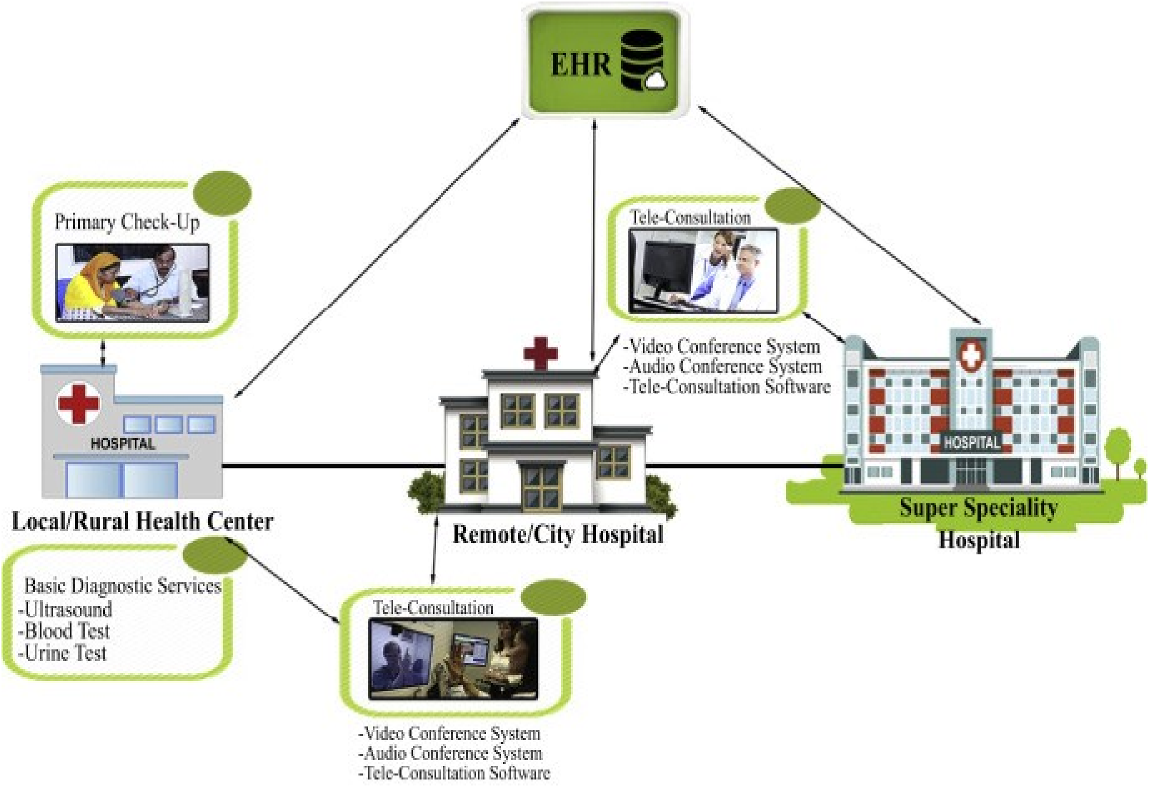


Figure 1.2 A general telemedicine system [4]

Fig. 1.2 shows a high-level outline of a typical telemedicine setup. The typical organisational framework for a telemedicine system consists of the following levels:

- Level 1: Center for local and distant telemedicine. These facilities serve as the primary care providers in non-urbanised or outlying regions.
- Level 2: City/district hospital. The local/rural clinics are linked to the regional hospital in the city/district. Establishing a link between the district and state hospitals is possible but not required.
- Level 3: Speciality centre. The municipal hospital has connections to other medical facilities that focus on treating specific diseases.

When an individual requires medical assistance, they visit the closest community health centre, where a local healthcare professional delivers care and conducts an initial examination. The physician uses live audio or video feeds and automated systems to communicate with patients in real-time. The essential diagnostic tools and teleconsultation gadgets are housed in this section, and they are connected to the city hospital through computers and the Internet. The primary role of the local healthcare unit is to gather and transmit essential patient information, such as physiological data and images, to the distant city hospital. The primary function of the local healthcare unit is to collect and send all of the patient's vital information to the faraway city hospital, including physiological data and pictures. After receiving the documents, the remote doctor will evaluate all of the information thoroughly before moving forward with any live interaction with the patient. After carefully evaluating the patient's condition, the doctor will arrange for the patient to visit a distant medical centre. All of the information pertaining to a patient is maintained in a centralised database that is accessible by all of the hospitals, no matter how far away they may be. The data is accessible via web-based or mobile app interfaces. The best hospitals also have connections to secondary facilities where patients may receive specialised care in times of crisis; these secondary facilities are equipped with teleconferencing equipment identical to the ones used by the top hospitals[4].

Telemedicine is healthcare delivery by electronic means, most frequently video conferencing [5]. Many healthcare facilities are looking towards telemedicine as a solution to rising healthcare expenses and the demand for improved treatment. Better access to healthcare has resulted from enhanced communication between doctors and their far-flung patients. Telemedicine has also been shown to improve connectedness, leading to fewer hospital readmissions and more adherence to treatment programmes. The improved access provided by telemedicine is not limited to patient-provider interactions. Telemedicine might help doctors form collaborative groups to share knowledge and improve patient care.

1.2.2 Applications of Telemedicine System

The following are the various applications of telemedicine systems listed below.

- 2nd Opinion
- Chronic Disease Management
- Device Streaming
- Disaster Relief
- Emergency Room (ER) Diversion
- Mobile Health
- Medication Management
- NICU/ICU
- Paramedic/Ambulatory
- Telemedicine for Remote Clinics
- Sharing Medical Information

1.2.3 Benefits of Telemedicine System

There are benefits to both patients and doctors when using this technology. Telemedicine may enrich and improve patient experience despite technological barriers and criticism. The field of telehealth, which includes telemedicine, has various benefits.:

- Better Assessment
- Better quality patient care
- Control of Infectious Illness
- Comfort and Convenience
- Extends access to consults from specialists
- Family Connections
- Increasing patient engagement
- More convenient, accessible care for patients
- Primary Care and Chronic Condition Management
- Safe Environment for Patients and Providers

1.2.4 Limitations of Telemedicine in Healthcare

Telemedicine has several potential drawbacks, especially when contrasted with more conventional care means. It has supposed to work in tandem with existing healthcare, not as a replacement. Using telemedicine via a public network or an unencrypted channel presents a significant security risk since hackers might potentially obtain access to sensitive patient information. This technology is not yet ready for widespread usage because of potential drug delays in emergencies. If a doctor is licenced in one state, but their patient lives in another, the doctor cannot treat them in the other state. The clinicians' telemedicine service should be secure, rigorous, and compatible with privacy regulations. Focusing on patient self-reports and requiring clinicians to ask additional questions during telemedicine meetings are essential for obtaining an entire medical history. If a patient fails to disclose a severe symptom that should have been picked up during in-person care, their medication might be ineffective. Not being easily accessible or inexpensive is a significant downside. Setup and maintenance costs for the provider might be high. Despite its apparent benefits, implementing telemedicine infrastructure might be prohibitive for specific clinics and hospitals. Unreliable care cannot be provided if there is a communication breakdown.

1.2.5 Future of Telemedicine in the Healthcare Sector

In the future, patients will quickly and easily create accounts and arrange appointments with their favourite providers. Scanning and uploading patient verification documents, medical reports, and old prescriptions saves patients the trouble of manually entering their information. With the support of the patient interface, the doctor may formulate an immediate treatment strategy. The patient's medical and personal history are summarised for the doctor's convenience. Getting urgent and routine medical care is easy because of the abundance of local facilities. As a result, doctors can spend more time in person with patients who need intensive care and less time on routine issues that can be resolved remotely. Patients will be triaged more efficiently with video consultations in the future, and those who do not need immediate care will be discharged from the ER faster. This leads to better patient outcomes and reduces the need for emergency department diversions. Many hospitals and clinics are using telemedicine software as a future-proofing measure. It connected cardiologists with patients willing to go to a remote clinic. They will work with the present system to shorten the intervals between follow-up visits. Many businesses may benefit significantly from the anticipated development of remote patient management as the sector's next driving factor in virtual healthcare.

1.2.6 Telemedicine Security and Privacy

Fraudsters frequently target healthcare institutions because of the high value of the information stored in their networks. Providers may only reap the benefits of telemedicine if they have a safe way to exchange patients' private medical data (PHI). Sensitive patient health information (PHI) must be safeguarded by HIPAA and other privacy requirements, making data security a primary priority in healthcare settings.

Encryption and other data security technologies can assist in ensuring the safety of sensitive patient data while in transit across IoT devices used in telemedicine. It has been suggested that using an edge server to store data before transmitting it to the cloud is one HIPAA-compliant telemedicine option [6]. This requires a comprehensive strategy that includes robust network security measures and managed access privileges.

1.2.7 Internet of Things IoTand Artificial Intelligence (AI) in Telemedicine

Nowadays, a wide variety of medical devices and equipment may be linked to a server or the cloud thanks to the advent of ultrafast connection made possible by the IoT. Hence, modern telemedicine may leverage real-time data to provide better remote healthcare. Wearables and other medical gadgets allow patients to monitor their vitals at home and send the data to their doctors for further examination. Providers can enter notes about patients, issue prescriptions, and add additional information that can be accessed by pharmacists and experts [7-8].

Patient's vitals are monitored continuously by integrated wearables, which then upload their data to the cloud for convenient, continuing examination by both patients and healthcare providers. Patients may make a telemedicine consultation whenever they feel poorly or have questions, and their doctor can access the ongoing readings to offer guidance. Better health management via this degree of monitoring can reduce the need for urgent care and emergency room visits for people with chronic diseases.

Patients now have access to a new method of communication with their doctors: self-service kiosks, which may be found in various settings, including clinics, pharmacies, and public areas. Patients may schedule appointments and make payments at the stalls.

For example, being able to act swiftly might be the difference between life and death in a heart attack or stroke. Telemedicine gadgets allow first responders to capture vital signs like EEG and EKG and send them to the hospital while still on the way. The team can better prepare for the patient's arrival and receive quick specialist advice on managing the patient.

The field of telemedicine is also benefiting from the advancements in AI. For instance, while taking a patient's medical history over the phone, AI might prompt the user with pertinent questions based on their previous answers. Artificial intelligence algorithms can also aid in diagnosis, which is especially useful for melanoma. Other AI-based applications can also provide medication reminders and recommendations for regular condition checks using information gathered from individual monitoring systems.

1.3 Machine Learning

1.3.1 Introduction

Machine learning is an AI application that has influenced various industries, from advertising and banking to video games and music. The healthcare sector, however, has felt the most extraordinary influence from artificial intelligence. PwC predicts that artificial intelligence will boost global GDP by $15.7 trillion by 2030, with the healthcare sector seeing the most significant benefit.

Machine learning is an expanding area of study with several practical implications. Machine learning is a subset of AI that allows computers to learn how to analyse data and identify patterns with little to no human input. Machine learning algorithms are trained by exposure to examples and data rather than given explicit instructions. Healthcare providers and healthcare systems will rely increasingly on machine learning technologies to sift through patient data and draw insights. Machine learning is crucial to the healthcare sector because it enables us to make sense of the voluminous volumes of healthcare data collected daily in EHRs. Machine learning techniques, such as machine learning algorithms, can be used in the healthcare industry to uncover previously hidden patterns and insights. As the use of machine learning expands in the healthcare sector, clinicians can take a more proactive tack, resulting in a more streamlined system with enhanced care delivery and patient-based practises [9].

Most artificial intelligence (AI) systems nowadays employ machine learning (ML) to analyse data and draw conclusions about the world. ML may be broken down into subcategories based on algorithm structure and learning technique. Supervised, unsupervised, and reinforcement learning are three further categories of learning strategies. The algorithm in supervised learning is taught via examples. Applications that have access to and can use previous data for predictions about future occurrences are good candidates for supervised learning. Even if data are incorrectly labelled or categorised, unsupervised learning algorithms can find a pattern in each dataset [10]. These algorithms train on past data, making their approaches easier to understand and implement. Regression algorithms and classification algorithms are two subsets of these. Regression techniques can be applied when there is a connection between the input and output variables, like weather forecasting. Classification algorithms divide the results into groups based on the values of input variables, such as yes/no or true/false. These characteristics make supervised learning ideal for predicting outcomes in practical situations based on input data.

1.3.2 Need for Machine Learning in Healthcare Organizations

In order to make sense of the vast volumes of healthcare data being created daily in electronic health records, machine learning is invaluable to the healthcare business. ML can be used in healthcare to uncover previously hidden patterns and insights. A more predictive strategy that unifies the system with enhanced care delivery and patient-based processes [11] is possible as machine learning in healthcare gets mainstream acceptance.

The healthcare system and its capacity to treat complicated disorders are continuously evolving for the better. Nevertheless, there are still numerous obstacles to overcome, especially when tailoring dosage and duration of therapy to individual features or for patient groups with limited clinical data, such as children. To forecast the best and most customised therapies for children, ML has been effectively implemented into paediatric care in recent years. ML has been front and centre since the spread of the COVID-19 pandemic. In an ever-changing and uncertain business landscape, many companies have turned to ML to streamline operations and drive R&D. Hospitals and health systems have benefited from ML's ability to tackle one-off problems.

One of the most promising areas of AI is ML technology, and many businesses are looking to take advantage of it. The number of people using ML is rising. It may be applied in corporate and medical settings and uses algorithms to promote data-driven learning. When new research, methods, and devices become available, healthcare evolves continuously. In some of these novel contexts, ML might help medical practitioners. Insights from unstructured text are now easier to develop and implement at scale, thanks to modern technologies. Millions of people's lives can be improved by the decisions that doctors and administrators make with the help of this new trove of ML-derived intelligence [12, 13].

Machine learning and healthcare principles have several significant applications in the sciences and the medical field. In healthcare, machine learning is typically used in three main areas: medical billing automation, clinical decision assistance, and the creation of clinical practice standards for use by healthcare organisations. Data generated by machine learning in healthcare can automatically recognise complex patterns, allowing primary care providers to receive clinical decision support directly within the electronic health record at the point of care.

1.1.2.3 Applications of Machine Learning in Healthcare

Healthcare organisations can better manage their data and provide better services thanks to the increasing number of machine learning apps.

- Managing Medical Data
- Helps in Medical Diagnosis
- Detecting Diseases at an Earlier Stage
- Medical Assistance
- Decision Making
- Personalized Medicine
- It helps Analyze the Errors in Prescriptions
- Improved diagnosis and disease identification
- AI-assisted surgery
- Medical research and clinical trial improvement:

1.1.2.4 Benefits for Healthcare Providers and Patient Data

Potential applications of machine learning in clinical care span a broad spectrum, from enhancing patient data and diagnosis to cutting costs and enhancing patient safety. Here are just some of the many ways that machine learning is improving the lives of medical professionals:

- Improving diagnosis
- Developing new treatments
- Reducing costs
- Improving care

1.4 Internet of Medical Things (IoMT)

1.4.1 Introduction

Connected medical hardware and software that can exchange data with HISes through the internet is known as the "Internet of Medical Things" (IoMT). An IoMT refers to the interconnected system of healthcare IT that includes Internet-connected medical equipment, hardware infrastructure, and software applications. Medical data may be analysed quickly and in various ways with the help of IoMT, sometimes called IoT in healthcare, since it enables wireless and distant equipment to connect safely over the Internet. Linking patients with their doctors and facilitating the transfer of medical data through a secure network can lessen the load on healthcare systems [14]

As seen in Figure 1.3, the IoMT market comprises intelligent devices used only for health care on the body, in the home, clinic, community, or hospital settings, and related telehealth, real-time location, and other services [15].

Figure 1.3 Internet of Medical Things at a glance [15]

The IoT has presented many new challenges recently, from smart homes to smart cities, including the IoMT. Improved quality of life and lower healthcare costs are only two of the many ways in which IoMT helps individuals. Essential components include wireless sensors, as illustrated in Figure 1.4, which can monitor a patient's health remotely, and communication technology, which may relay that information to carers.

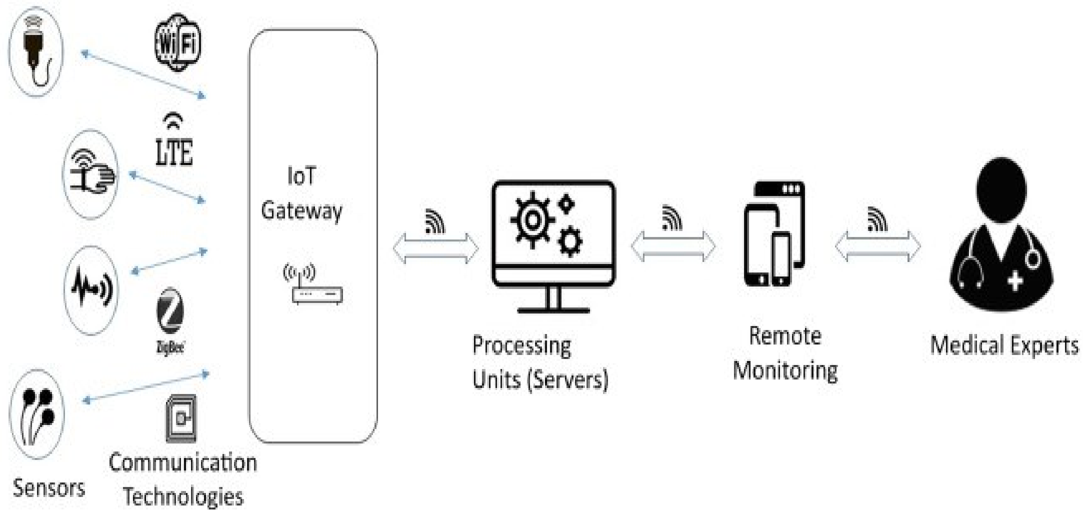


Figure 1.4 General architecture of the internet of medical things [16]

The first step in creating an intelligent healthcare ecosystem is realising the potential of current technology to provide superior service to end users and enhance their quality of life. Artificial intelligence is another enabling technology for IoMT, which may aid doctors in making clinical decisions and other complex tasks. The data provided by healthcare experts and patient input may be used by Machine and Deep Learning approaches to teach computers how to make normal and aberrant judgements. Artificial intelligence-enabled IoMT devices provide constant patient monitoring. The older people with disabilities can benefit from intelligent robots, smart homes, and virtual assistants. [16].

Figure 1.5 depicts the three primary components that make up the IoMT architecture: the application layer, the perceptual and the network layer. The perceptual layer is the lowest and is responsible for taking in information directly from the source and forming an opinion based on that information. There are now two parts to the perception layer: the access sublayer and the acquisition sublayer. The data collection sublayer's primary responsibility is to make sense of the obtained data by employing various medical perception and signal-collecting tools. Main signal acquisition techniques [17] may include graphic code, RFID, GPRS, etc.

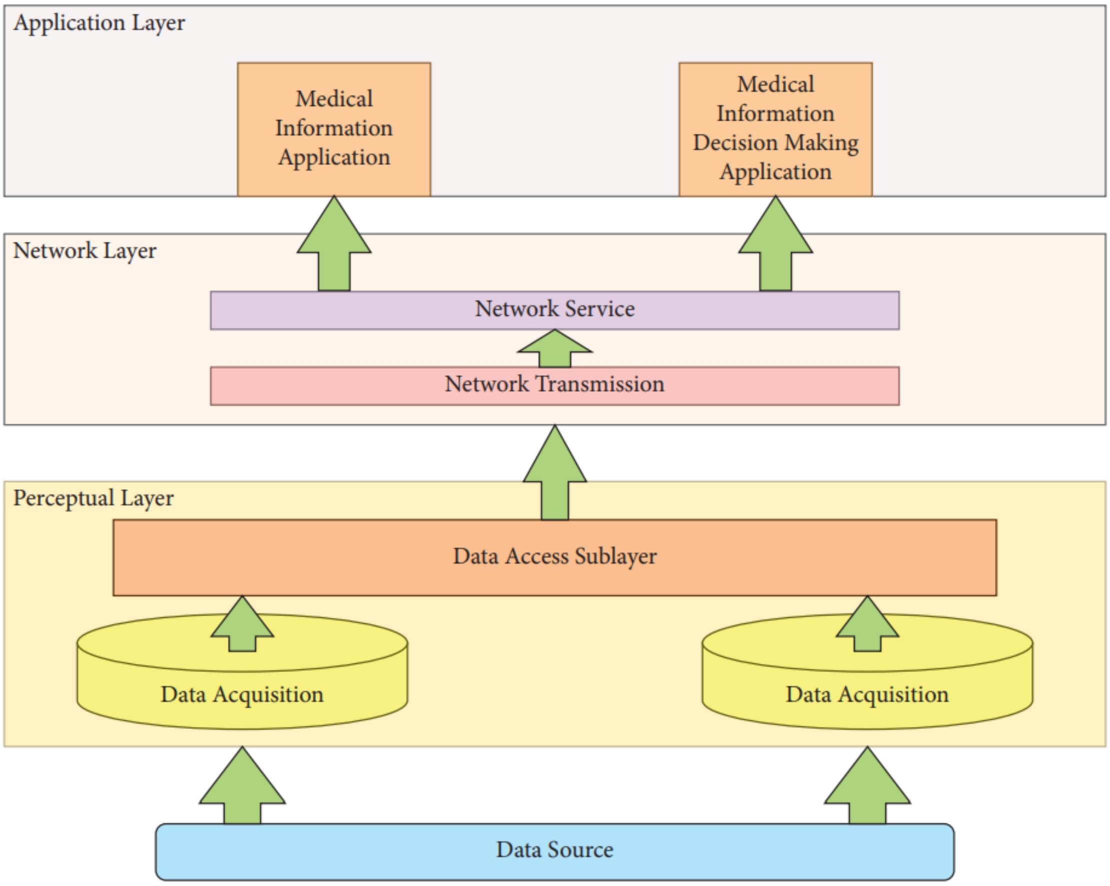


Figure 1.5 Layer-wise architecture overview of IoMT [17]

The data access sublayer uses short-range data transfer methods like Bluetooth, Wireless Fidelity (Wi-Fi), ZigBee, etc., to link the information gathered in the acquisition layer with the information in the network layer. The network layer, or intermediate layer, offers several data transmission methods and a variety of platform and interface-related functions. The Service and Network Transmission Layers are sub-layers of this layer. The network transmission sublayer uses several mediums, such as mobile communication networks, wireless sensor networks, and the internet, to relay the perception layer's data in a timely, reliable, and impenetrable fashion. However, the service layer makes the unification of disparate systems possible, including databases, data warehouses, and information description formats. The platform offers an open interface and other platform-related services for these integrations. Again, this layer is divided into two smaller layers: the layer responsible for making decisions about medical data and the layer that stores and displays that data. The application layer takes the data collected from the network layer to administer the medical record through various apps. Patient records, including those for hospital stays, clinic visits, and other medical care, are kept in the in-depth files that comprise the medical information application layer. When it comes to medical care, however, it is the application layer that does the heavy lifting of analysing data on patients, ailments, medications, diagnoses, treatments, and so on [18-19].

1.4.2 Role of IoMT in Remote Patient Monitoring

The IoT has made it feasible to monitor patients worldwide remotely. A patient's health may be continually monitored using gadgets in the house and sophisticated sensor technologies, allowing for prompt intervention in the case of medical emergencies.

Patients are increasingly active participants in their care because of the IoT. Patients are more encouraged to take charge of their physical and emotional wellness with fitness bands and other technologies.

Keeping patient data safe online is paramount in remote patient management. Patients are monitored constantly to ensure their physical safety and prevent any accidents from occurring. Patients get a more optimistic outlook and are motivated to take active steps towards healing as a result [20].

1.4.3 Challenges in IoMT

The Internet of Medical Things (IoMT) might dramatically improve patient care but poses new concerns. Successful healthcare IoT implementation relies on overcoming these obstacles. Due to the vast number of participants in the IoMT ecosystem, IoT presents its own set of legal, regulatory, technological, and privacy issues:

- Connectivity providers

- End users
- Medical device providers
- Original equipment manufacturers (OEM)
- System integrators
- Systems/software providers

In order to effectively address these issues, healthcare institutions, technology providers, lawmakers, and regulatory agencies will need to work together. The full potential of IoMT can only be realised if privacy and security are prioritised if adequate investment is made in data management systems, if interoperability is fostered, if costs are taken into account, if environmental impacts are addressed, if scalability and upgradeability are ensured, and if clear regulations and standards are established. In the long run, this will result in better patient treatment, higher quality medical results, and a more streamlined healthcare system.

1.4.4 Benefits of IoMT in the sector of healthcare

The Internet of Medical Things (IoMT) is the network of interconnected medical devices and health systems that can generate, analyse, and transmit health data to healthcare information technology systems, such as wearables and sensor-enabled devices for remote patient monitoring applications. By allowing for remote patient monitoring and the transfer of medical data over a secure network, Wi-Fi-enabled medical equipment that promotes machine-to-machine communication minimises the strain on healthcare systems and the number of in-person visits patients require. There is no denying the impact IoMT is having on the healthcare system. IoMT is ideally positioned to improve healthcare systems in various ways, including cost savings, simplicity of care delivery, and satisfaction of customers. The following are some of the benefits of IoMT in the medical field.

- Asset Management
- Customized treatment
- Better Chronic Care Management

- Ensures Adherence to Physician’s orders
- Improved Health Outcomes
- Improved Drug Management
- Increased Patient Engagement
- Reduced Costs
- Real-time Monitoring
- Remote Medical Assistance

1.5 Fog Computing

1.5.1 Introduction

Fog Computing distributes the information-sharing and management responsibilities over the whole network. It improves the efficiency of cloud management by providing more nuanced data. Fog computing is a virtualized platform that provides resources, including processing power, application interfaces, system management, and storage. The company's administration describes the relationship between IoT connections and cloud-based systems. Fog computing becomes increasingly important when delivering applications and services to a larger audience in a distributed setting. In consumer devices like wristwatches, fog computing displays information about the user's activity, such as the distance walked and the number of calories ingested. The device monitors heart rate and adjusts the user's sleeping environment accordingly. Nowadays, smartphones like the Samsung Note 4 include built-in sensors like heart rate monitors and motion detectors like accelerometers and gyroscopes. Reducing idle cloud workers is a boon to fog computing, a comprehensive part of distributed computing when both registration phases have similar admissions. Distributed computing has strengths and flaws that come together to produce a package that benefits and hinders end users. One of the advantages of the IoT is the efficient creation and management of massive volumes of data in various applications, which can then be quickly processed and analysed. Particularly amid the dynamic progression of human existence, novel care frameworks are needed. Medical care frameworks might benefit from increased efficiency when fog processing and IoT are used in devices used in clinical sector applications [21, 22].

As shown in Fig. 1.6, the three levels that make up the usual architecture of an IoT/fog Computing-based healthcare system are various layers: the sensor layer, the fog layer, and the centralised cloud layer for computation.

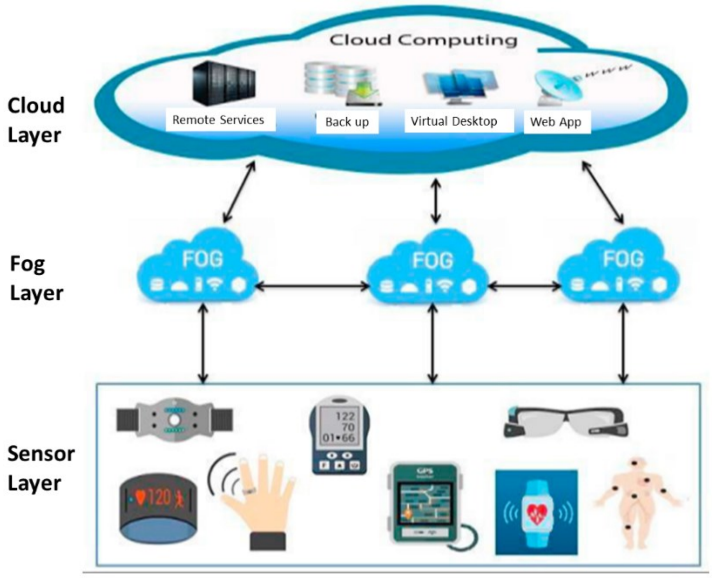


Figure 1.6 The Architecture of Healthcare System based on IoT/Fog Computing.[23]

Data from medical sensors and devices is sent to the fog layer for processing and execution over a wireless (Wi-Fi) or cellular (4G/LTE) connection. The health data acquired by different IoT medical sensors and equipment is sent to the cloud computing layer, which the fog computing layer "acts as a bridge between. Its purpose is to analyse healthcare data from the IoT in real time. Real-time messages or alerts are sent to users concerning whether or not they are currently considered infected. Since it is linked to the cloud, this layer may store data, run analyses, and compile patient medical records. Fog computing represents a shift in the computer paradigm. The Fog is typically depicted in popular culture as a low-lying cloud. For end-user applications like healthcare, autos, and intelligent cities, fog computing entails placing computing services on faraway devices to support low latency, high efficiency, and high dependability [23]. Fog computing is a sort of cloud computing in which a "smart gateway" performs a number:

- Computation: The data is processed by a fog gateway, which then generates logs of a medical grade that are sent to the cloud for further analysis. The calculations have a wide range of complexity, from filtering to wavelet analysis.
- Data Security: Users may set up a shield that safeguards their information and identities.
- Local Connectivity: The fog gateway communicates wirelessly with wearable sensors to collect data and trigger events like warnings and notifications.
- Onsite Database: It generates a locally accessible database with features and clinical parameters for internal and external queries.[24]

1.5.2 Fog Computing in Health Monitoring

The use of fog computing has set a new benchmark for the healthcare monitoring industry. Fog computing alleviates the strain on networks by processing data decentralised. The remote healthcare system employs sensors implanted in or strategically placed on the patient's body to monitor their health, measuring specific symptoms and supporting them in obtaining precise remedies. A dedicated device facilitates interaction between the sensors and the monitoring apparatus [25].

1.5.3 Solution to Overcome the IoT Challenges

IoT security challenges

Fog computing is a proxy for low-powered devices needing software or authentication updates. In addition, they can check on the safety of adjacent electronics.

Latency Constraints

To accommodate the latency requirements of IoT applications, the fog executes all time-sensitive processes close to end users.

Network Bandwidth Constraints

Application requirements, network capacity, and available computing resources are all considered in a fog computing setup. As a result, less information must be sent to the cloud, which frees up bandwidth.

Uninterrupted Services

Fog computing may function autonomously, guaranteeing service uptime despite erratic cloud connection speeds.

1.5.4 Role of Machine Learning (ML) in Fog Computing (FC)

In addition, the variety and transmission efficiency of FC services should be improved. The creation of FC systems has made use of ML. Hence, ML may help in many different ways for nodes. For instance, by incorporating ML with FC, deep analytics becomes applicable. As ML can provide trustworthy AI, developers are creating intelligent fog apps. These algorithms mine collected data for insights and insights. Fog computing is essential for enhancing network traffic and response times by decreasing latency during the execution of any job. Fog computing's primary goal is to relieve stress on the cloud by distributing low-latency processing tasks. However, there have been occasions when Fog computing has failed to deliver sufficient and precise findings, diminishing efficiency and quality in performance processes.

High-layer services, in-depth analytics, a robust end-user, and intelligent answers are required of Machine Learning applications employed in fog computing. This is why ML may be used to improve the throughput and latency of data transfer in Fog nodes. With user-defined real-time processing and communication operations, it enhances the architectural sequence of Fog nodes. Machine learning's use has been on the rise, and not just to enhance fog computing applications. It is also being put to work to improve fog services, such as resource management, security, energy efficiency, latency, and traffic modelling. Our current work seeks to fill this knowledge gap by examining the function of Machine Learning inside the fog computing paradigm. The relevance of Machine Learning in edge computing is highlighted, and the three critical components of fog computing that Machine Learning is connected with controlling are precision, resources, and security.

1.5.5 Characteristics of Fog Computing

A fog system has several features, as listed in Table 1.1.

Table 1.1 Fog computing characteristics

Features	Description
Heterogeneity	It is at the very end of a network that provides services to a very diverse set of customers.
Capability	It provides instantaneous reaction, making it useful in a variety of industrial contexts.
Storage and Services	It has its own data processing, storage, and communication infrastructure.
Operation Areas	Works only in the immediate area (single hop from a device to a fog node)
Platform	It has a highly virtualized platform.
Additional Features	Provides low-cost, versatile, and transportable hardware and software deployment.

1.5.6 Benefits of Fog Computing

- It protects data more effectively since businesses may analyse their information in-house.
- Due to the data's proximity to the host, security is enhanced.
- The quantity of information that must be uploaded to the cloud is decreased.
- Reduces the response time of the system.

- Network bandwidth is conserved since less data needs to travel a shorter distance.

1.5.7 Limitations of Fog Computing

- In addition to storing and processing data, data transfer also requires encryption and decryption to unlock data, adding another layer of complexity to data management.
- Adding a layer of separation between the host and the cloud causes an increase in power usage.
- The host and the fog node may have congestion due to increased traffic (heavy data flow).
- Task scheduling involving the host, fog nodes, and the cloud is challenging.

1.6 Motivation and Significance of Work

Because of advancements in telemedicine, distant doctors may virtually visit patients whenever they are in need. Medical experts and patients can have a face-to-face, or at least virtual, consultation using video or audio conferencing technology. As hospitals, providers, and patients all learn to work together in the context of today's healthcare system, the benefits and uses of telemedicine are expanding. Some of the motivational reasons for the integration of telemedicine and machine learning are:

1. Improving healthcare accessibility: Telemedicine can enhance healthcare accessibility by connecting patients with healthcare services. By utilizing machine learning techniques, we can contribute to advancing telemedicine systems that facilitate remote monitoring, diagnosis, and treatment, effectively bridging the gap between patients and healthcare providers.
2. Enhancing diagnostic accuracy: Machine learning algorithms can analyze extensive medical data, identifying patterns and making precise predictions. By developing telemedicine-specific machine learning models, we can assist in

improving diagnostic accuracy, enabling healthcare professionals to make well-informed decisions even from remote locations.

3. Remote patient monitoring: Machine learning algorithms can effectively analyze real-time patient data gathered through wearable devices or sensors, enabling continuous remote patient monitoring. By researching telemedicine systems that integrate machine learning, proactive monitoring can aid in the early detection of potential health issues, facilitating timely intervention and preventing complications.
4. Advancing healthcare research: Through research endeavours in telemedicine, including exploring new algorithms, models, and techniques, we can expand our understanding of how machine learning can address specific healthcare challenges. This research holds the potential to inspire new methodologies and drive further innovation within the healthcare industry.

By combining the capabilities of telemedicine and the intelligence of machine learning, we can significantly contribute to the early diagnosis of illnesses, which is crucial for patients' chances of survival. Integrating health-parameter-based early illness diagnosis with telemedicine has the potential for a broader impact on the healthcare industry, paving the way for improved methodologies and innovative solutions.

Hence, early sickness diagnosis may be crucial to a patient's chances of survival. Thus, we require health-parameter-based early illness diagnosis.

1.7 Challenges and Issues in IoT and Telemedicine

Paying doctors and other medical professionals for telemedicine services might be difficult. For instance, Medicare only partially reimburses telemedicine providers. Not having your electronic health record (EHR) system linked with the platform you use to deliver telemedicine services might lead to data inconsistencies in the workflow. Without proper platform integration, the continuity of care might be jeopardised. It is possible that a patient's new telemedicine provider will not have access to their whole medical history if they transition from one service provider to another. Patients who do not know how telemedicine functions are less likely to use it. I have a tough time getting to them. Before launching telemedicine services, polling your patients to determine which devices they are most likely to utilise is essential.

High-speed data transmission, monitoring, storage, and calculation are required due to the volume of data generated by IoT devices. Connecting data acquired from disparate sources and using standard medical service frameworks adds complexity to data integration. The risks associated with the IoT have increased because of cyber security concerns, the use of IoT in an inadequately standardised security protocol, and hackers gaining access to too much sensitive data. The IoT and its associated devices require constant updates, inefficiently managed inventories of patients or assets related to healthcare, a lack of attention to market interest, subpar products and services, the compromise of customer data set frameworks and security breaches. Outdated security network measurements are another primary difficulty with IoT applications in healthcare organisations. The IoTs require a secure network of interconnected devices and the safekeeping of sensitive information. Organizations providing healthcare services put a premium on patients' right to confidentiality and safety. Due to the importance of protecting patients' personal health information, medical data transmissions across international borders must always be encrypted.

Installing various devices or accompanying sensors was an essential aspect of IoT because only a limited number of medical facilities required connections and alliances. In addition, the same patient may be suffering from several conditions. Such discrepancies might lead to aberrations and misunderstandings in the application of IoT devices in healthcare initiatives.

1.8 Research Problem

Currently, telemedicine frameworks are utilized for far-off sound and video interviews, lessening the expense of rehashed visits to the specialist, constantly checking patients with persistent infections, distant careful activities, and crisis care in mishap circumstances, just as for preparing and improving the capabilities of specialists. In telemedicine frameworks, clients can share network assets such as electronic clinical records, clinical reference books, chart books, strategies, and suggestions and provide details regarding clinical investigations and other clinical data. These data assets, spoken to in data sets and data distribution centres, are made accessible to wellbeing offices through the presentation of data and correspondence innovations and the advancement of wellbeing network foundations. Telemedicine has two associations: "doctor-patient" and "doctor-doctor." The first kind of communication is effectively utilized in various countries. It permits doctors to talk about the aftereffects of tests, leads distant discussions with tight masters, screens the methods and tasks, and gives preparation and accreditation of the clinical workforce. The second kind of communication has shown up generally as of late, which is brought about by the need to address various issues, both emotional (for instance, trust in the specialist or doctor) and target (for example, protection of patient data). This communication allows us to unravel various undertakings: gathering data (grievances, anamnesis), assessing the outcomes and changing treatment, dynamic about a full-time visit, and checking the well-being state. One of the principal disadvantages is cost and availability. Although telemedicine is an outstanding and remarkable service, it may be too expensive for businesses to use and maintain more minor medical services. So, introducing an intelligent expertise system at the intermediate layer, i.e., the fog layer, will reduce cost and increase reliability.

Information quality is an issue in medical care-related tasks; if the information totals are utilized to investigate initially and analyze the information perceptions, the meaningful choices taken on such peculiar information may turn out badly. Mainly, when information related to Big Data is heterogeneous and multidimensional, the information investigation might be wrong. Being IoT geologically worldwide, it is fitting to facilitate the intricacy of Big Data with IoT and their related medical care information and related Fog Computing administrations before their perceptions are taken for understanding. Recognizing the worth and unimportance of similar medical care information is imperative since both are basic in our perception and understanding examination, affecting the emotional cycle. The examination questions are planned to keep in mind the writing studies and the inspiration of new advancements in medical services sciences. How do the IoT-driven medical care frameworks oversee in a sheltered and secure climate? Why do we need a system, and how can it work? How does Fog Computing discover multidimensional ailments?

These extra loopholes in the present computing models create another computing and networking paradigm named Fog. A fog computing stage runs the same application anywhere in the closeness of the clients, settling on constant examination and dynamic more achievable and successful. Also, fog as a service empowers new IoT-based medical care models to convey computing, control services and storage at various scales to address the issues of different end clients. Considering these realities, we proposed an IoT-Fog-based medical services structure to distinguish and control disease prognosis. The framework alerts patients, users, and doctors during a crisis. It additionally helps with diagnosing stage and persistently checking users' health boundaries utilizing IoT-based clinical sensors to anticipate the danger of assault. It empowers the maturing populace or people who are disabled and live alone or distant from medical care specialist organizations to deal with their health more productively and viably, even in remote places.

1.9 Research Contribution

The research presented in this study offers several significant contributions to telemedicine and healthcare. The key findings and advancements include:

- An approach is proposed to integrate IoT, fog computing, and artificial intelligence in telemedicine, which opens up new possibilities for extending healthcare services to rural areas with limited resources. This is made possible by leveraging the extensive computing capacities offered by diverse healthcare organizations.
- The research has contributed to the development of an innovative architecture for a Telemedicine system called IFCATS (Internet of Things enabled Fog Computing-based Architecture Telemdecine System), representing a significant advancement in telemedicine by facilitating proactive healthcare and

empowering healthcare providers with the capability to detect diseases remotely but also ensures robust security measures are in place to protect sensitive medical data.

- The study presents a noteworthy research contribution in the form of an intelligent hybrid framework named Ensemble Machine Learning Regression with Fuzzy Logic Inference System (EMLR-FLIS) for remote disease prediction. By integrating ML techniques and FZI, this framework significantly enhances the accuracy of disease prediction. This advancement holds great potential to benefit patients with similar diseases and improve human health.
- The proposed system's performance has been rigorously evaluated by comparing multiple classification methods based on various performance parameters, including the confusion matrix. This analysis helps identify the suggested system's effectiveness compared to existing methods.

The following are some of the most significant contributions made by the suggested method:

- Development of a new classification system for epilepsy identification based on routinely monitored health indicators.
- A novel detection technique is introduced utilizing machine learning, fuzzy logic, and sensor data fusion.

In conclusion, this research contributes valuable insights and practical implementations to telemedicine, IoT, fog computing, and artificial intelligence. The findings demonstrate the potential for enhanced healthcare services, remote disease prediction, and improved diagnosis techniques, ultimately benefiting patients and promoting better overall human health.

1.10 Objectives

1. To study and analyze existing telemedicine systems for different wireless network technologies.

2. To develop Internet of Things (IoT) enabled Fog Computing based architecture of Telemedicine system for diseases diagnosis and to monitor remote health care services.
3. To develop and analyze machine learning-based fog computing for an efficient e-healthcare system.
4. To evaluate and compare the proposed method with existing methods regarding confusion matrix, receiver operating characteristics, latency, and energy consumption.

1.11 Thesis Organization

This thesis consists of six chapters, as discussed below:

Chapter 1 explains the research's background and motivation. It also outlines the research goal and the scope of work that will guide the study. It also describes the importance of the fundamentals of the proposed system keyword technology with its architecture and various features and significance related to the domain.

Chapter 2 contains a literature review of existing works on IoT-based real-time health parameter monitoring, considering health records and classification of disease diagnosis using various intelligent techniques, fuzzy logic, machine learning, and deep learning approaches.

Chapter 3 explains the proposed layer architecture based on fog computing with the working flow. Primarily, real-time data acquisition from sensors, built based on a wireless body area network, is performed and observed on the IoT Cloud dashboard platform data.

Chapter 4 provides a detailed implementation of an intelligent disease diagnosis model using hybrid intelligent techniques, supervised classification-based machine learning algorithms, and fuzzy logic. Further, the results are evaluated and analyzed for hybrid algorithms combination.

Chapter 5 is based on the simulations, and multiple classification methods are compared by the various performance parameters primarily based on the confusion matrix and analyze the proposed system performance with existing methods.

Chapter 6 emphasizes the main accomplishments and utility of the research and discusses the scope for developing future research work that could apply to designing the intelligent telemedicine system.

CHAPTER 2 REVIEW OF LITERATURE

2.1 Literature Review

In this section, a literature review of various telemedicine application scenarios is conducted, which is primarily based on IoT and ML.

Health informatics, public health, law, medicine, the trade press, and industry reports were among the numerous fields in the literature on information security and privacy in healthcare that were studied [26] (2010) from information systems journals. In addition, they offered a broad perspective on the state of the art in information systems research and proposed novel avenues for investigation.

Pulse oximetry variables normal range determined [27] (2010) in a small group of individuals with chronic obstructive pulmonary disease. Exacerbation onset was separated from symptom change using a composite HR and SpO2 score, which might allow for more timely treatment and validate such occurrences in therapeutic studies.

Hamida EB et al. [28] (2011) use time-variant channel measurements at 2.45 GHz to conduct experimental research on the topology dynamics and performance of routing techniques in WBSNs. They plan to learn more about how delivery ratios, latency, and energy consumption are affected by human body shadowing in network and routing systems. Finally, some best practices for developing and deploying WBSN architectures are outlined.

By employing a body sensor network platform we previously built, they could determine the respiratory rate from three-dimensional acceleration data by using an adaptive band-pass filtering approach in conjunction with principal component analysis [29] (2011). Twelve people were tested in person to confirm that the method can accurately estimate the subjects' respiration rates while sitting, standing, walking, jogging, or sleeping.

Patients with COPD on home oxygen treatment can keep track of their respiratory frequency [30] (2012) daily. These individuals' breathing rates dramatically increase days before ECOPD necessitates hospitalization. If this is the case, there may be a chance for preventative measures.

In-home HF and CLD telemonitoring has significantly enhanced [31] (2013) the proportion of patients who do not require hospitalization and lowers disease-specific hospitalization rates and lengths of stay in the hospital. Telehealth monitoring in the home has the potential to be an effective alternative method of providing medical care for frail older adults.

A system comprising many wirelessly networked medical sensors and a controller device has been suggested to collect medical data in real life [32] (2013).

The method proposed [33] (2014) for securing transmitted data by generating pair symmetric keys for the sensor and the receiver. Since each person's biosignals are distinct, they yield the data required to generate cryptographic keys. During processing, a mathematical model was used to create the time series that are diagnostically comparable to the original biosignals.

Patients with persistent heart failure are the focus of a meta-analysis of remote patient monitoring done [34] (2014).

To lessen the burden on battery life in WSNs, Chang J-Y et al. [35] (2014) suggested a uniform clustering technique combined with an energy-efficient routing design—the centralised and cluster-based methods used to design the sensor nodes' cluster-tree routing architecture. Using ideas of uniform cluster organisation, this system aims to lessen the distances sensor nodes must travel when transmitting data. An optimal cluster distribution may be achieved by calculating the distances between sensor nodes and considering their respective residual energies when deciding which nodes should serve as cluster heads. The data transmission lengths were shortened between the sensor nodes by utilising an adaptive multi-hop strategy predicated on the standard cluster position. By distributing the load among the clusters, the overall energy consumption can lower and increase the lifetime of the sensor nodes. The simulation findings demonstrate that the suggested strategy improves the existing methods for wireless body sensor networks regarding energy efficiency and longevity.

The reliability of a vest was tested [36] (2015) when the wearer is lying down, sitting, standing, and walking. They compared the Hexoskin wearable vest's ability to track heart rate (HR), breathing rate (BR), tidal volume (VT), minute ventilation, and hip motion intensity (HMI) when the subject was lying down, sitting, standing, and walking to gold standard laboratory equipment.

There is a potential for widespread adoption due to the analysis of security difficulties and challenges presented [37] (2015) and the provision of a clearly defined security architecture that ensures the privacy and security of users.

The OSI model's seven-layer design broke in a recent assessment [38] (2016). OSI, or the Open System Interconnection Reference Model, is a reference framework for making protocol judgements in a well-organized system.

Even below the current air quality recommendations, short- and long-term exposures to outdoor air pollution worldwide are linked [39] (2016) with the mortality and morbidity of COPD sufferers. Using biomass for cooking in low-income countries was strongly correlated with COPD mortality among adult female nonsmokers.

In order to address these concerns, an energy-efficient information-sending technique (EDFS) is proposed [40] (2016) for modifying sensor energy usage and enhancing network lifespan and communal duties in heterogeneous WBANs. Two of our primary promises are compacted detection to reduce the size of the initial physiological data that must be communicated and that the excess energy levels are considered the examination of recurrence. Data transmission via WBAN networks may be made more efficient and reliable with the help of the EDFS. Similarly, simulation findings demonstrate that the proposed EDFS can successfully manage the often-shifting WBAN landscapes while delivering tailored energy consumption and productivity.

Damian Dziak et al. [41] (2017) presented an indoor/outdoor IoT-based information system. Due to the absence of methodological approaches to the design process shown by the performed survey of comparable works, a design methodology is developed, which approaches the design target from the perspectives of the stakeholders, contracting authorities, and possible users. The approach uses a three-axis acceleration and magnetometer, thresholding, the Pedestrian Dead Reckoning (PDR), and a decision tree algorithm. A monitored individual may be accurately located inside one of four room zones, and their falls and behaviours of laying, standing, sitting, and walking can be identified with such an architecture. The discovered behaviours are then utilised to categorise the present state of affairs as either normal, suspicious, or hazardous, and the system then sends an alert to the healthcare professionals. The suggested solution's strong resilience was verified in real-world circumstances. In addition, the test results encouraged future participation in the project and pleased stakeholders and potential consumers.

K Vani et al. [42] (2017) designed a method to transmit temperature and heart rate data from home monitoring devices to carers. In addition, the indoor air quality is monitored and set off an alarm if a potentially dangerous gas is identified. The temperature, heart rate, and gas sensor data are continuously monitored and analysed using a fuzzy logic method. The Thing Speak service provides access to cloud-stored information. Anomalies will be identified based on the learned data and the sensor data.

A comprehensive system for seizure detection using DL was established by Gramacki et al. [43] (2017). The R and Python codes provided enable the following tasks: reading raw European Data Format files, reading data files containing the seizure annotations made by human experts, extracting train, validation, and testing data, creating an appropriate Convolutional Neural Network (CNN) model, training the model, checking the quality of the neural classifier, and saving all learning results.

A. Al-Khafajiy et al. [44] (2017) investigate the creation of a Cognitive Fog (CF) model for safe, smart healthcare services that can make their judgements, such as whether or not to continue operating processes, what new methods to invoke when necessary, and how to safeguard the system's operational procedures.

AI and telemedicine's malleability opened up boundless possibilities for progress [45] (2018). Constant monitoring, medical care data innovation, intelligent help conclusion, and data examination coordinated effort are four themes in the spread of this technology's use. The patterns of late writing and the problems they aim to solve will be addressed, along with examples.

W. Liu et al. [46] (2018) proposed edge-device-driven architecture as an alternative web-based e-health object connectivity and service delivery framework. The updated approach was developed to facilitate the use of recently implanted health objects, accommodate the growth of edge devices, and provide specific procedures for establishing further e-health intelligence standards. With various edge devices and implanted oversaw objects coordinated at the core link.

M. Singh et al. [47] (2018) tackled such fundamental problems using a look-up table and energy harvesting. It provides the highest possible throughput while using as little energy as possible, making it possible to build self-sustaining, all-encompassing wireless networks. There have been three settings for the experiments. The impact of varying various system parameters on the performance of critical components like lookup tables and energy harvesting has also been studied (like energy consumption, normalised throughput, and saved and residual energy). NS-2 runs the simulation, and MATLAB displays the data for maximum readability. By comparing the suggested model to the baseline model, the results show that it utilizes less memory.

The architecture of microservices [48] (2019) enables early defect localization and determination on a remotely managed virtual recovery machine through an Internet-based communication channel. The architecture above comprises three layers: a base layer that collects data from the repair machine's subsystems using IoT standards, a middle layer that analyses the collected data to determine the part's health, and a top layer that presents the results. At last, the higher layer makes decisions based on the findings. The proposed engineering makes sense for non-uniform systems. This study also demonstrates how this engineering accommodates the specific and all-encompassing safety procedures for mission-critical devices like medical service guides.

The 5G-enabled Tactile Internet (TI)-based telemedicine procedural architecture for Healthcare 4.0 is analysed and discussed by Gupta et al. [49] (2019). They provide an ongoing review of the historical setting of the first successful cardiac surgery. 5G's URLCC management ensures a reliable communication connection for a remote medical operation with a latency of less than one millisecond and availability of 99.99%. A solution for a telemedicine procedure includes a correspondence station with two unique components: a traditional organisational structure and a TI enabled by 5G. With TI as the organisation's backbone, the proposed design is more responsive and reliable in the research. The last section highlights some of the most pressing unanswered questions and assessment challenges of the conventional telemedical process design, focusing on inactivity and consistency.

O. Medical care administration application advances in telemedicine engineering have been studied by S. Albahri et al. [50] (2019). IoT arrangements have established problems relating to wearable body sensors (Tier 1) and clinical focus personnel that plague telemedicine designs (Tier 3). To sum up, a potent examination strategy demonstrated the Fault-Tolerant-Framework on mHealth assumed (FTF-mHealth-IoT) about IoT to identify critical flaws in the current investigation into medical care administrations.

To facilitate remote verification of the real restoration measure, S. Ashapkina et al. [51] (2019) have examined the task of developing quantitative measures for automated recognition of activity kinds inside the framework's architecture. The research suggests limiting capacity attributes to the base twisting approach by using the computation of time scale distorting with distinct measurements. This study aims to provide methods for measuring the accuracy with which restoration practices are carried out following treatment protocols, thereby increasing the controller's objectivity and reliability.

Incorporating a stage for guiding rescue vehicles is proposed with precision and keeping an eye on passengers' tolerance levels [52] (2019). The scene's primary goal is to increase the patient's chance of survival by having the ambulance arrive at the hospital as soon as possible, giving the watchful doctor as much time as necessary to review the patient's biological data. That way, the doctor may give the paramedics helpful instructions for the ride or arrange for the necessary clinical services to be ready for the patient when they arrive. Moreover, the platform employs AI techniques on the collected data to aid the specialist in identifying probable clinical hazards. The framework's blueprint provides us with a multi-tiered approach. The presentation of a model of the integrated framework is evaluated.

The term "beneficial arrangement" [53] (2019) is used to describe a device that serves as both a checking and video-conferencing tool for patients and doctors care specialists who are involved in the care of multiple patients and as a legitimate, user-friendly instrument for the chronic patient. The advantages of this setup are distinct from those of other telemedicine platforms and also include monitoring the progress of at least one PDTA in which the individual patient is included, verifying the adherence to care plans (pharmacological and electro-clinical overviews) and adjusting them based on clinical perceptions; and, finally, reducing the variability of the risk list of comorbidities, the simultaneous presence of multiple pathologies, which is a common prognostic.

Using the OSI reference model, a hierarchical organisation for the framework suggests [54] (2019) under study, depicting the many stages of information disclosure. Each successive level of the proposed model highlights the tasks involved in ensuring the secure connection of the components of the telemedicine system. Examples of secure organisation collaboration in setting up remote human state monitoring at varying information introduction levels are provided. A set of techniques and computations for implementing such an association are offered to ensure the safety of data transmitted through unencrypted channels.

It is critical to have access to an Ophthalmologist on call for remote screening of patients for potentially vision-threatening disorders when providing care in Medically Underserved Areas/Population (MUA/P) or high-stress clinical settings like emergency rooms [55] (2019). With an estimated 217 million people globally afflicted by moderate to severe vision-impairing illnesses, the availability of speedier (or continuous) diagnoses for a broad scope is crucial for the growing number of patients with vision-impairing infections. Early identification is essential in preventing vision loss from diabetes-related retinopathy and AMD (age-related macular degeneration).

Y. Fan et al. [56] (2019) explored wearable medical devices (WMDs) on the path to telemedicine restoration. The WMDs and the traditional devices could estimate the patients' vital signs, including ear temperature, heart rate, blood oxygen saturation, and pulse. The calculations were done at six, ten, fourteen, and eight o'clock on the first day of each month of 2018. By comparing WMDs and conventional devices, no significant difference was found in the intended information and estimating season of any key sign ($P > 0.05$); nevertheless, the WMDs consumed much less time in the information record and the total estimation measure. This proves that WMDs may be used for critical sign estimation in telemedicine therapeutics.

The designers increase accessibility between devices, customers, and companies utilizing the IoT [57] (2019). A central component of this system is a Raspberry Pi, which collects data from the sensors and processes it to control things like lights, fans, doors, alarms (in the event of an emergency), phone calls, and television. The individual's carers, loved ones, or friends can gain insight into the person's health thanks to sensors attached to a crisis module. It monitors the person's vitals and notifies the proper authorities if a problem arises.

D. Gracanin et al. [58] (2019) look into how technology might deliver healthcare services while maintaining privacy and safety. Successful, ongoing help with the adaptability to meet unanticipated needs and emergencies can be provided by an appropriated VCC (DVCC), which is composed of individual VCCs and the junction of local and public edges. A meta-model-based discussed approach to managing private patient data and enhancing the efficacy of the care community's faculty will allow off-site care facilities to expand to meet the rising demand for round-the-clock monitoring.

The framework [59] (2019) provided the automated detection of anomalies/illness deteriorations using a specialised clinical Decision Support System and a clinical specialist UI. The gathered data included heart rate, respiratory rate, body posture, oxygen saturation, electrocardiogram leads, auscultation, and electrical impedance tomography. Pilot concentrations of the framework were implemented in Greece and the United Kingdom. The pilot project was conducted in Greece, highlighting the journey from data collection to applied translational medicine via the first operational use of the WELCOME Foundation.

The current state of utilising the achievements of current Internet advancements analysed [60] (2019) following the tasks of telemedicine screening of patient's condition and to investigate the potential for deciding approaches to enhance the quality of telemedicine benefits by constructing modern telemedicine structures. It is recommended to study leading global nations' best practices and analyse the benefits of leading telemedicine screening for various patient categories to determine the major directions for enhancing telemedicine administrations in Ukraine.

X. Li et al. [61] (2019) provide secure and proficient data on the executive's framework dubbed EdgeCare for adaptable healthcare infrastructures. Local experts are prepared to organise frontline staff to manage healthcare data and promote information sharing. EdgeCare is designed for real-world application through a collaborative effort, including engineers at several levels. They use an electronic clinical record to illustrate how sensitive data relating to healthcare is handled. The Stackelberg game-based improvement calculation is also guided by them toward an optimal motivation system for an information authority and customers in the appropriate decentralised information exchange. From there, we investigate safe data exchange and participation in the framework. Mathematical results from a security audit demonstrate that EdgeCare provides practical solutions for safeguarding healthcare data and encouraging expert knowledge sharing.

The framework of IoT telemedicine medical services for the elderly living alone is presented [62] (2019), which may be used for the living arrangements of seniors alone. Pulse monitoring, myoelectric signal collection, and a bloodstream monitoring infrastructure are the primary foci of the telemedicine system. Older people who live alone often rely first on common physiological signals. The patient's body has calmed down (showing no unusual signs) and is now at its baseline norm physiologically (Base Line Data). From the patient's vantage point, the physiological symptoms are confirmed and presented on a mobile device.

With a Bluetooth preparation card, data on the patient's systolic and diastolic pressures and pulse may be sent in stages to a remote worker through a phone network under an e-health paradigm [63] (2019). As a result, the model may transmit and report through an instant message a separate warning if an irregularity should occur in the estimation and reporting of the elements. These records are then stored in a database where the patient and specialist can consult and view them from any Computer. A small number of patients who followed the programme saw very positive results. In addition, there was a discrepancy between the used pulse screen and one guaranteed by the World Health Organization, with a difference of +/- 5 points being within the margin of error.

The particular methodologies pertinent to the mHealth application investigates and proposes [64] (2019), which allows patients to send health records to specialists and specialists to offer the history further and haggle with masters and help patients find companions experiencing primary indications in protection saving climate guaranteeing the wellbeing record's credibility.

Telemedicine research has been developing for some time now [65] (2019). This research aims to compile a list of, and settings for, the most often used electronic cards and microcontrollers in remote monitoring systems for chosen chronic patients' vital signs. Similar to this investigation, the reasons, obstacles, and suggestions for further study were proposed to be differentiated. There is no starting point from which the people who want to research this subject should employ equipment and programming tools.

To enhance fall detection, anticipation, and security, Md. Shahiduzzaman et al. [66] (2019) offer a cloud-network edge engineering that incorporates the clinical cloud, edge organisations, and end gadgets like a smart protective cap. Wearable cameras, accelerometers, and spinning sensors are included in the smart helmet so that it can monitor the older adult's daily activities via data gleaned from various sources. Offloading the processing of sensor data preparation to the edge can reduce latency and increase security. The clinical data can be sent through a secure clinical network to the clinical cloud for services like fall alerts.

With the help of a sensor for estimating oxygen saturation in the blood (SpO2), another for measuring temperature, and another for measuring blood pressure, as well as Bluetooth, an Arduino, and some apps, a groundbreaking IoT architecture is suggested [67] (2019). The suggested device with sensors and innovation-based data is most suited for special patients' health observation and analysis, according to the purposeful outcomes and its assessment.

Wijesinghe et al. [68] (2019) offer an autonomous framework they term an Intelligent Diabetic Assistant (IDA), which prioritises analysis and therapy based on what it sees on the user's screen. Information-based modules in the IDA allow for limited screening, near-native foot ulcer diagnosis, and severity-based orders. They quantify the IDA's usability in terms of execution, learnability, and satisfaction using the System Usability Scale (SUS). They conduct our experiments with medical professionals who are concerned about diabetes. With an average SUS of 88.5, the framework was adequate but not very convenient.

Zhao et al. [69] (2019) offer a wearable system that uses accelerometers and AI to monitor foetal growth. A local checking unit and a remote health assessment unit comprise the framework. An article of clothing equipped with accelerometers for data security, an installed framework for signal handling and artificial intelligence (AI), and an Android-based nearby checking stage used for the perception of insights on foetal wellbeing status based on data obtained from the garment via Bluetooth make up the community monitoring team. The IoT is used in the framework to interface all the terminal checking units to a control community, which is essential in grasping the concept of the eHealth home consideration.

In the context of Next Generation frameworks, Cecil J et al. [70] (2019) discuss an IoMT-based framework for surgical training. This Internet of Medical Things framework is designed and developed with the ideas of Global Environment for Network Innovations (GENI)-based networking in mind. Virtual reality (VR) simulation settings with haptic interfaces allow orthopaedic experts and residents to learn and communicate with one another from different places and in real-time. The results of these studies highlight the possibility of adopting such Internet of Medical Things-based methods to medical education and show the need to employ such a framework in medical education.

IoT conceptualization, definitions, features, technologies, and difficulties are illustrated by Abdel-Basset M et al. [71] (2019). They also discussed how the IoT may help us make better decisions in our daily lives and create a more intelligent educational system.

Health risk assessment and decision-making (Health-RAD) is an algorithm proposed by Habib C et al. [72] (2019). It checks in on a patient, calculates the severity of their illness based on their vital signs, and if there's a serious problem, it alerts the doctor immediately. As a result, the patient's condition is constantly evaluated, and his or her progress or decline is tracked. A risk variable between 0 and 1 reflects the severity degree. If the danger value is high, the patient's condition is extremely serious and immediate medical intervention is required. A vital sign's score is based on historical and present values, so we can evaluate its health by tracking its trajectory over time rather than only reacting to spikes.

The throughput, power, and latency requirements for constantly monitoring BSNs using BLE technology were investigated by Ayoub MAM et al. [73] (2019). They assess multiple Bluetooth core standard implementations using a Nordic Semiconductor nRF52840 chip-based theoretical model and experimental equipment. They assess an EKG gateway and node's current consumption and battery life and examine how BLE versions and settings affect electrocardiography (EKG).

Using the wireless power transfer (WPT) method, Rabby MKM et al. [74] (2019) offer a unique, aware priority schedule-based charging algorithm for recharging embedded sensor nodes in a wireless body area network. As a result, the instantaneous power needs and the total power consumption of SNs during particular operation times are all regarded as crucial study performance metrics.

The technical concepts and distinguishing features of intelligent wearable devices are dissected by Li P et al. [75] (2019). A smart wearable equipment system for Power Patrol operation has been designed to support intelligent patrol inspection at power network operating sites.

C.C. Bennett. Cardiovascular, Neuropathy, Ophthalmic, Renal, and Other Complications were identified by et al. [76] (2019). The modelling technique employed machine learning strategies, including unsupervised clustering, supervised classification, natural language processing of unstructured care notes, and feature engineering. Predicting the onset of diabetic complications using claims data or data on socioeconomic determinants of health was successful around 83.5% of the time, the study found. They also demonstrated that significant clusters in the patient population associated with problems and mental health may be revealed and exploited for cost-effective screening programmes, cutting the number of patients tested by 85%.

A great quick medical response strategy is proposed by Sundaravadivel P. et al. [77] (2019), which keeps tabs on residents' vitals and provides feedback or hospital notifications as needed. The suggested architecture delivers multi-dimensional feedback to guarantee people's safety and caution them against developing health problems. Simulating the proposed architecture with the ZigBee radio standard took 95 seconds with 40 nodes. Using the free software CupCarbon, we show how these sensor networks may be routed according to the severity of an emergency.

For wireless body area network applications, Miran MM et al. [78] (2019) developed a new and downsized PIFA (Planar Inverted-F Antenna) that operates at the ISM band (2.4-2.4835 GHz). The suggested implantable antenna has real dimensions and a slot-less ground plane, simplifying the construction. The suggested antenna's compact size makes it ideal for WBANs or wireless body area networks. The patch of the proposed antenna is made of copper, while the substrate is made of Rogers RO3210. The antenna is encased in biocompatible Rogers RO3035 so that it does not come into touch with the human body. CST Microwave Studio was used to conduct analyses of the antenna's operating frequency, Voltage Standing Wave Ratio (VSWR), S11 parameter, directivity, and overall efficiency in flat and bending configurations on a three-layer human tissue model. In order to alleviate any antenna-related health worries, the Specific Absorption Rate (SAR) is calculated.

Craig Kuziemsky et al. [79] (2019) discuss the potential reach of AI approaches in the telehealth field. These approaches are oriented toward satisfying clinical requirements, and they shed light on current directions based on reports of recent developments. There are now two main areas of concentration for linked modern orders. First, there was the need to enhance the quality of standard clinical practice and service delivery. Second, innovative models of care needed to be created and supported. Specific case studies have been selected to illustrate each area of interest better.

H. Chen et al. [80] (2019) presented a new approach to recognising wheezing, crackling, and other common noises by combining the optimal S-transform with deep residual networks. The experimental findings demonstrate the superiority of the suggested OST and ResNet for the multi-classification of respiratory sounds, with an accuracy of 98.79%, a sensitivity of 96.27%, and a specificity of 100%. The deep-learning-based ensembling CNN and empirical mode decomposition-based ANN are outperformed by 3.23% and 4.63%, respectively, in respiratory sound triple-classification by the suggested method.

Prediction of cardiovascular disease was proposed by R Latha et al. [81] (2019) using a partially observable Markov decision process model (POMDP). Fog computing lets the doctor reach the patient in an emergency. Due to the patient's condition, an ambulance was sent. iFogSim, a fog computing platform, sends clinicians data. Academics are becoming interested in fog computing in healthcare. Cardiovascular disease is widely studied. Blood viscosity increases cardiovascular disease risk. Blood moves slowly and frictionally due to its high viscosity.

Using statistical modelling in the form of quadratic discriminant analysis and audio-based signal processing techniques by J McNulty et al. [82] (2019). The overall accuracy of this 3-class classifier was 85.35% (testing dataset). The detection sensitivity for both inhalation and blisters was 70%. By giving doctors a quick and easy way to track whether or not their patients are using their inhalers as prescribed, this strategy has the potential to make a big difference in clinical practice.

The importance of characteristics taken from the various phases of a CO_2 waveform shape from an exercising asthmatic is investigated by OP Singh et al. [83] (2019). In the proposed study, nine volunteers with stable mild asthma, aged 20-25, were randomly selected from the UTM Health Center and breathed into human respiration CO_2 monitoring equipment before and after training. The participants ran on a medical treadmill for 2 minutes at 7.5 km/h (TMX428-15% elevation). Then, they compared the Area generated from each segment using numerical methods to the slope or derivative of the program, automatically segmenting each breath cycle into sub-cycles using a threshold. By analysing the receiver operating characteristic curve, they discovered that the segmented portion of the mixture of the upper expiratory and alveolar phases had a greater area under the curve (AUC) of 0.94.

There are 1.84 million tweets that are many years old and deal with health that were recovered by Talpada et al. [84]. Their research indicates that without a sufficiently extensive and uniformly distributed training dataset, lexical and semantic-based approaches to sentiment prediction perform better than Deep Learning approaches. They found that the number of domain-specific terms in the target text significantly impacts the accuracy with which sentiment can be predicted using domain-specific information. Predicting sentiment using Twitter data can reveal patterns in the demographic distribution of feelings. They found that many people have favourable impressions about telemedicine. It is in its early stages and has not yet reached a broad audience.

An autonomous system, the Intelligent Diabetic Assistant (IDA), selects the diagnosis and the treatment priorities based on the observations that are displayed on the screen in the proposed prototype by I Wijesinghe et al. [85] (2019). The IDA is built around knowledge-based modules for things like foot ulcer detection and border screening in near real-time, categorization based on severity levels, and clinical decision support. To evaluate the IDA's usability, they applied the System Usability Scale's (SUS) three subscales: performance, learnability, and satisfaction. With a mean SUS of 88.5, the system is usable but not outstanding. They conduct their studies with doctors and nurses who have experience treating patients with diabetes.

L Yung-Hui et al. [86] (2019) proposed a novel paradigm for autonomous DR diagnosis, leveraging AI and the cloud. The max-pooling layers are swapped out in the DCNN for factional max-pooling. To discover the true limits of each class's distribution,a support vector machine (SVM) was used for training. With the help of the provided strategy, the recognition rate was able to increase to 86.17%. They are also making an app for the iPhone. A non-specialist may take fundus pictures and automatically make a diagnosis using this device called the "Deep Retina," which is equipped with a portable ophthalmoscope. It is a telemedicine system that can be used in real life, and it has applications in self-diagnosis, remote medical treatment, and care at home.

The gradient boosting decision tree (GBDT) with EIMO device data predicted blood pressure rates by B Zhang et al. [87] (2019). EIMO hardware collects electrocardiogram (ECG) and photoplethysmogram (PPG) signals. Without overfitting, cross-validation selects the optimal settings. GBDT's systolic and diastolic blood pressure predictions are above 70% and 64% accurate, respectively, with a prediction time of less than 0.1 s.

Lateef HA et al. [88] (2019) investigated three alternative classification algorithms using an open-access EEG dataset consisting of pre-identified records of 500 patients: SVM, Logistic Regression, and Long Short-Term Memory (LSTM). Models were adjusted with pre-existing Python library code and the orange data mining program.

Pravin A. et al. [89] (2019) suggested a smart and secure healthcare architecture based on fog computing to anticipate and prevent Dengue virus outbreaks.

A novel EoT computing platform for safe and intelligent healthcare monitoring services is presented by Alabdulatif et al. [90] (2019). Data saved and processed within an IoT framework encrypted with fully homomorphic encryption will remain private. Our framework significantly improves the speed with which encrypted data is processed without sacrificing the analytical precision or privacy of the information being processed. To collect and analyse the large-scale and heterogeneous data in the dispersed EoT devices independently before sending it to the cloud, a distributed strategy for clustering-based approaches is developed for the proposed EoT architecture. They show how the suggested framework works in practice by analysing a case study including bio-signal data from a patient.

A. Kallipolitis et al. [91] (2020) detail the design and implementation of a telemedicine-based emotional assessment programme. They discuss the finer points of the suggested plot's employment and fusion, outlining the repercussions of the plot's pinpoint accuracy and dynamic nature. Two separate methods are employed and compared. To identify seven distinct assumptions about human looks, the principal technique takes advantage of the fast and stable qualities of the accelerated robust highlights computation. The implementation of the latter requires convolutional neural networks. During routine video chat sessions between authorised clinical staff and patients, the complete usefulness is provided as a Web administration to the medical care stage.

Innovative engineering (SENET) [92] (2020) based on artificial intelligence techniques and consisting of three main layers is anticipated to be presented. Following detailing the proposed architecture, they investigate the presentation of four effective and well-known calculations for protecting WBSNs with k head bunches: severe world difficulties (WCC), molecular swarm enhancement (PSO), insect province advancement (ACO), and genetic estimate (GA) (the k-inclusion issue). Results demonstrate that the suggested design reduces power consumption by distant sensors. The WCC computation is a good option for determining sensor placement in the proposed engineering concerning WSN power consumption, the total number of sensors needed, and consistent quality. Results demonstrate that the suggested WCC computation, with an average score estimation of 38.44 across 9 cases, is superior to alternatives.

Fog computing, powered by the IoT, is being developed in the healthcare sector to streamline administrative processes for the general public, which might ultimately save the lives of billions of people. The method is geared toward making mathematical operations more convenient to data repositories in healthcare facilities [93] (2020). One area of focus is finding ways to send data to the cloud more cheaply.

The proposed blockchain-based solution [94] (2020) has the potential to revolutionise healthcare management. To eliminate the need for a centralised administrator, they suggest a setup in which Ethereum keen agreements are used to construct a simple, sealed telemedicine medical services framework and to guarantee the integrity of sensitive patient information. The patient is kept thoroughly apprised of all transactions in the organisation, and the communication between all the groups affiliated with the organisation is directed by the sharp agreement.

Fog computing, IoT, and AI are all used in a new framework presented in [95] (2020) to provide superior and more intelligent insight into medical services. The implementation of Blockchain technology ensures the building's safety. The suggested approach makes primary ICU patient surveillance more efficient and safer. The design is functional for anybody in the ICU, from patients to doctors to chaperones. In this scenario, IoT devices continuously monitor patients' vitals and transmit that data to fog nodes for processing. Several AI processes are run in the fog's nodes to determine if the perceiving patient needs immediate attention.

A solution was provided for integrating electroencephalography [96] (2020) based on AI components into the eHealth IoT framework using the TensorFlow open-source platform. Certain physiological data, such as systolic and diastolic blood pressure, blood oxygen saturation, heart rate, breathing force and rate, skin conductance and opposition, internal heat level, and electroencephalography (EEG) from different anodes, are recorded using this framework. Our major focus is developing an EEG-controlled device that can decode eye movement as part of our ongoing research on mind-computer interfaces.

Using statistical and machine learning strategies [97] (2020) within a mobile app to categorise ADLs is also possible. Because of the increased need for continuous, non-invasive monitoring during the current COVID-19 epidemic, MyNeuroHealth was developed, considering the disproportionate prevalence of neurological diseases in developing countries. The outcomes demonstrate that MyNeuroHealth can recognise and classify Motor Seizures and falls with 99% accuracy. The software can also tell whether a patient has fallen or staggered for whatever reason and informs carers accordingly.

A broad overview of helpful technologies and frameworks provided [98] (2020) for addressing the COVID-19 crisis in various contexts. The main focus is specifically on 1) wearable devices suitable for checking the at-risk and isolated populations, both for assessing the health status of guardians and the board workforce and for encouraging emergency measures for admission to emergency clinics, and 2) covert detecting frameworks for recognising the infection and for observing patients with moderately mild manifestations whose clinical circumstance could out of the blue deteriorate. Finally, new challenges and opportunities for future directions are highlighted.

A continuous home telemonitoring framework was presented [99] (2020) for chronic respiratory patients utilising a Vodafone-developed 5G network as part of the Italian Ministry of Economic Development's 5G Experiment in Milan. The user wears a respiratory and activity screen, a natural sensor, and a heartbeat oximeter that sends data to a Vodafone 5G foundation Multi-Edge Computing worker. Data about activities, respiration, and the surroundings is continually relayed and gathered. Eighteen healthy subjects were examined for 48 hours in unmonitored accounts.

A novel system was developed [100] (2020), facilitating information's seamless transmission and display across various complex frameworks. The system demonstrated successful data transmission and reception over distances of 300 km, with an approximate delay of one second. Additionally, the study monitored the system's processing power, memory usage, and data preparation time as the user count increased. Each client typically transmitted 810 bytes of data, encompassing client ID, timestamp, channel data, breathing rate, and sleep status. With a capacity of ten concurrent users, the study recorded an average data preparation time of 0.15 seconds, an average CPU utilization of 5.01%, and an average memory utilization of 0.1%. These findings highlight the need for careful management when considering the future applications of this groundbreaking technology in terms of individual, public, and therapeutic use.

The AIR CARDIO project evaluates [101] (2020) the efficacy, efficiency, and practicality of a home telemonitoring system for congenital heart disease children. Biomedical sensors send ECG, pulse rate, core body temperature, weight, and oxygen saturation to a central location. The centre's attention remains aligned with e-health care, allowing doctors greater freedom in determining a patient's limits. Via the app, parents and guardians are also given a few questionnaires to complete to gauge their level of satisfaction with the system as a whole. The Monasterio Foundation for Pediatric and Adult Congenital Cardiology at the University of the Caribbean enrols 45 individuals annually for the clinical trial. The fundamental results include the selected kid-friendly sensors and the incredibly user-friendly smart central point technology.

The HEREiAM platform supports many data innovation frameworks [102] (2020) developed the technical considerations and user experience evaluation of the platform's telephonic verification features. The newest medical services guidelines and security standards are met by a private cloud that receives data in the form of XML files from off-the-shelf Bluetooth clinical devices and uses them to create an interoperable health administration framework. This Android-based framework integrates many utilities to aid the elderly who live alone and is designed to be accessible via TV and small devices.

A stable COVID-19 observational framework is proposed by M. Otoom et al. [103] (2020). The system has five main components: the Quarantine/Isolation Center, the Data Analysis Center, the Health Doctors, the Cloud Infrastructure, and the Center for Collecting and Downloading Data on Symptoms. The proposed framework would utilise an IoT system to collect real-time indication data from clients to early distinguish suspected COVID cases, monitor the treatment response of the individuals who have just recovered from the infection and comprehend the concept of the infection by gathering and analysing important data. After selecting the most important symptoms, a test was designed to evaluate these eight formulas using real-world COVID-19 adverse events data.

Once restrictions on staying at home are eased, [104] (2020) proposed a consumer hardware solution to promote safe and stable entry points. EasyBand, an IoMT-enabled wearable, is familiar with reducing the emergence of new sure instances by automatic contact following and facilitating fundamental social removal.

S. Vishnu et al. [105] (2020) edition analyses and diagrams IoMT-based remote monitoring frameworks, including ingestible sensors, smart clinics, portable healthcare, and better continuous illness treatment approaches. Security concerns limit buyers' IoMT use.

The focus and QRS band have been eliminated thanks to cutting-edge technology. Human bio-impedance signals are filtered out using texture cathodes [106] (2020), and human breathing indicators are recognised using discrete. A reflection-type photoelectric sensor is used to decipher the impact of the human heartbeat signal, and ECG (Electrocardiogram) data is combined with a constant assessment of the sleeve-free circulatory strain based on the beat wave conduction time. The smart blood oxygen immersion computation will have a self-learning limit calculation based on close infrared image plethysmography signal box discovery.

Sundaravadivel P. et al. [107] (2020) suggested a privacy-protected framework to track a traveller's medical care. iMED-Tour, the tour wearable created as part of the study, alerts the user to seek a hospital service in an emergency and offers recommendations for the user's chosen medical services. The suggested framework's response time and capacity to locate the quickest route were assessed. CupCarbon's implementation of the shortest route method took 10 seconds, whereas the iMED-Tour wearable's delay was milliseconds.

Using a look-up table, O. I. Khalaf et al. [108] (2020) investigated the SE and EE concerns in 5G networks using a fuzzy-based technique and found that a symmetrical trade-off between the two was optimal for improving system performance. The simulation is performed in NS-2.31 and then analysed and displayed the data in MATLAB. The suggested model obtained maximum values of EE and SE of 0.92 bit/J/Hz and offered a QoS-provisioned cognitive radio-enabled 5G network.

Data dependability may be confirmed by a three-tiered decision-making process proposed by Tao H. et al. [109] (2020). Using simulations for 1-DM, 2-DM, and 3-DM, they assess system efficacy and demonstrate that up to 92% of data dependability problems may be uncovered across all three levels. Notwithstanding extensive research on security and privacy procedures, the system would be the first framework to address data dependability specifically.

A. Duggento et al. [110] (2020) demonstrated that a machine learning-based cardiac classification tool may be employed as a diagnostic and screening tool in various situations, including telemedicine, by reaching an area under the ROC curve of 0.77.

Bahaa Mostafa et al. [111] (2020) presented an IoMT-based healthcare monitoring system that would be assessed by AI utilising fuzzy logic. The proposed effort relied on an ATmega microcontroller to carry out its functions and provide a platform for monitoring analytics (decisions) to be made by carers or doctors. In this article, we select a heart rate pulse sensor and an infrared temperature sensor that report skin temperature and ambient temperature to the carer.

Ahmed Kassem et al. [112] (2020) designed a low-cost, high-quality multipurpose wearable revolutionary system for cardiac patients and fitness athletes. The proposed fuzzy logic system architecture successfully identifies the physical mobility mode, and the IoT dashboard remotely monitors test participants' health states in real time.

Kashif Hameed et al. present an innovative and intelligent healthcare system powered by cutting-edge technologies like the IoT and ML.[113] (2020). A medical decision support system can benefit from this system's sensing and processing capabilities. This technique offers an inexpensive option for those living in far-flung places, allowing them to determine whether or not they are experiencing a severe health problem and, if so, to seek treatment at local hospitals. The experimental outcomes also demonstrate that the suggested system is effective and smart enough to perform medical services. The findings in this research provide empirical support for the hypothesis.

To facilitate effortless communication between the BCI and IoT gadgets, O. P. Idowu et al.[114] (2020) presented an enhanced Particle Swarm Optimization (PSO)-based neural network (NN). To conduct the trials, a BCI system was built that first projected features extracted from the PSO into a neural network and then used the network to interpret the user's intentions. The experimental findings showed that the suggested PSO-based NN approach could effectively categorise motor imagery (MI) tasks with a 98.9% accuracy. Several suggestions on how the work may be improved were also made.

T. Malapane et al. [115] (2020) revealed the system's design, its implementation, and preliminary testing with result analysis. The sensing and networking parts of the system's infrastructure are outlined. The experimental results of testing the intelligent algorithm based on fuzzy logic for spotting out-of-the-ordinary situations are provided.

To monitor thousands of older people, identify falls, and alert caretakers, Dariusz Mrozek et al. [116] (2020) demonstrated a scalable system architecture. Scalability tests were also run, considering the need for full transparency to make large-scale system operations possible. In addition, they tested several Machine Learning models for their detection efficiency and verified the best ones. The classification performance of the tested models was best with Boosted Decisions Trees. They also conducted experiments to ensure that fall detection worked both in the Cloud and on an Edge IoT device. Tests of data transfer from the device to the cloud indicated that executing fall detection on the Edge reduced the size of stored and communicated data.

ML Rahman et al. [117] (2020) presented a machine-learning illness symptom analysis approach to aid patients in finding the right medical speciality based on the symptoms they can quickly identify. The suggested framework would employ a machine learning method to choose which medical speciality to refer the patient to after considering their unique set of symptoms. They use nine distinct supervised machine-learning methods to probe the proposed architecture. The framework's effectiveness in determining the correct medical divisions using machine learning approaches is investigated and contrasted. This framework has applications in both automated healthcare administration and telemedicine platforms. Perhaps this might pave the way for significant progress in the healthcare industry.

Automatic seizure identification employing DL methods and neuroimaging modalities was the subject of a detailed review by Shoeibi et al. [118] (2020). Methods are reported that use EEG and MRI to diagnose epileptic seizures automatically.

Seizure identification using electrical activity features in the brain is the subject of research by M. Savadkoohi et al. [119] (2020). Neurophysiologists will find rewarding careers in the rapid and precise diagnosis of epileptic seizures. They investigated the most effective method for identifying significant patterns in epileptic EEGs. The signals utilised in this study are 173.61 Hz sampled chunks of 23.6 s taken from 100 single-channel surface EEG recordings. Five normal volunteers with eyes closed and open and five epilepsy patients with seizure-free periods and epileptic episodes provided the signals. The EEG waves were analysed, and their features were extracted using a Butterworth filter, Fourier Transform, and Wavelet Transform in the frequency, time and time-frequency domains, respectively, for feature engineering (SFFS). We used the SVM and KNN learning algorithms to identify the processed EEG data. Three metrics—Accuracy, Sensitivity, and Specificity—were used to evaluate performance. After experimentation, SVM performed somewhat better than KNN.

A unique heterogeneous deep ensemble-based multi-feature learning environment for epilepsy classification is proposed [120] (2020). The suggested model addresses data imbalance, low precision, and the necessity of a trustworthy classification model. To do so, they sample data with a 95% confidence interval and employ a multi-level augmenting strategy to deal with the issue of class imbalance. Random sampling, down-sampling, and synthetic minority over-sampling are only a few examples of the many methods used to collect samples (SMOTE).

The Bonn University database was used in the assessment of the system by Khati R.M. et al. [121] (2020). In pattern recognition challenges, choosing the right features to analyse is crucial. They utilised a wrapper approach based on recursive feature elimination to narrow down the most valuable features. In this research, they tested seven different machine learning algorithms on data derived from human brain activity (EEG).

The suggested architecture presented [122] (2020) ensures privacy and granular access control using a highly efficient key exchange protocol and ciphertext attribute-based encryption (CP-ABE). Together, CP-ABE and digital signatures safeguard the system's integrity and its users' privacy. The suggested framework's safety and efficiency were also evaluated.

A safe and fog-assisted architecture addressed security, access control, and privacy issues in PHR systems [123] (2020). The proposed framework is built on a fog-based architecture and employs ciphertext attribute-based encryption (CP-ABE) and an efficient key exchange protocol to ensure privacy and granular control over who may access what. To further protect the integrity of the system and the privacy of its users, CP-ABE is employed in conjunction with a digital signature. The safety and efficiency of the suggested architecture were examined.

EHR systems' security and privacy features are the exclusive topic of a comprehensive literature evaluation conducted [124] (2020). Before delving into the possible uses of blockchain in EHR systems, they provide a brief overview of the foundational knowledge between electronic health record (EHR) systems and blockchain. Several research possibilities and obstacles are also highlighted.

The use of machine learning methods for large-scale data analysis in healthcare was recently reviewed in depth by Wei Li et al. [125] (2021). In addition, the benefits and drawbacks of current methods and the many obstacles still standing in the way of further study are emphasised. This research will aid healthcare professionals and government agencies stay abreast of the newest relevant data analytics developments based on machine learning for intelligent healthcare.

Machine learning-based healthcare systems are first categorised [126] (2021). Pre-processing data methods, learning methods, evaluation methods, and applications are the main pillars of the proposed taxonomy for ML-based schemes in healthcare diagnosis treatment. Certain papers published in machine learning's healthcare applications are reviewed in light of the suggested categorization. Researchers may use the information in this paper to get up to speed on the most recent findings about ML's medical applications, understand the obstacles they face, and plan for future studies.

M. Jayalakshmi et al. [127] (2021) offer an all-encompassing approach to tracking the physical and mental health of COVID-19 patients. It makes it easier to provide better medical treatment, especially to those who have been isolated due to the COVID-19 outbreak. A fuzzy context-aware reasoning engine-based model uses the patient's present context and behaviours to determine their physical and mental state. Patient condition detection is aided by a fuzzy reasoning engine using language rules based on inference processes. The fuzzy set properties of various context types are used to frame linguistic rules. The reasoning engine guarantees accurate real-time context interpretation and current assessment using fuzzy semantic rules to detect the link between the qualities. The results of a simulated experiment are evaluated with the help of a context reasoning system based on fuzzy logic. The findings support continuing to track COVID-19 patients in their present settings.

Ihsan Ullah et al. [128] (2021) proposed a data fusion method using type-2 fuzzy logic (T2FL) and Dempster-Shafer theory to extract particular data and get the proper conclusion quickly. Type-2 fuzzy logic properly determines patient data membership values, and the DST appropriately fuses and processes the membership values to conclude. Computer simulations with heart disease and diabetes datasets reveal that the proposed strategy outperforms ontology and type-1 fuzzy logic systems in precision.

To address patients' demands while guaranteeing quick storage decisions even when data flows from wearable devices, Vinodhini Mani et al. [129] (2022) created a novel predictive model of health data storage.The machine learning classifier was built using a training set constructed from a subset of experts showing strong correlations between health data and storage characteristics. The outcomes validate the machine learning approach.

H. Harb et al. [130] (2022) suggested an effective sensor-based data analytics paradigm for real-time patient monitoring and assessment. The proposed system involves emergency detection, frequency modification, and real-time patient prediction. Our methodology outperforms other methods in simulations using real health data.

Using a novel paradigm, Raj Jennifer S. et al.[131] (2021) recommended boosting edge cooperative network performance. This improves peripheral computing. This initial step establishes partnership evaluation criteria. Maximising edge cooperation improves job performance. Real datasets from older adults's wearable sensors indicate the system's efficacy. Thorough experimentation supports the recommended optimisation technique.

J Hariharakrishnan et al.[132] (2021) extensively examines 6LoWPAN and RPL IoT in healthcare contexts. This research tracks athletes' body temperatures. Marathon runners can also develop race-topographic abilities differently. Athletes get sensors implanted to monitor their core body temperature during training. After analysing each athlete's thermoregulation process, tailored training regimens are created to accommodate variances. This strategy provides more customised progress tracking with fewer coaches and medical professionals, preventing premature deaths of healthy athletes.

AI for COVID-19 diagnosis and therapy was restricted by Samer Ellahham et al. [133] (2021). Deep Learning might automate COVID-19 diagnosis with powerful algorithms for finding subtle patterns in patient radiographs. Biomarker analysis and machine learning aid prognosis and therapeutic planning. Deep neural network-based pneumonia diagnosis has a sensitivity of 85.35% and a specificity of 92.1%, outperforming RT-PCR.

To remedy the deficiency in healthcare, Annamalai. M. et al. [134] (2021) presented a project to create a prototype pillbox. In addition to the medication, the hospital or retirement home may also supply this gadget, which has several high-tech functions. The majority of over-the-counter drugs, vitamin supplements, and stimulants should be compatible with this pack. The proposed smart pillbox has a programme that lets medical staff or patients customise the pillbox's settings, including the pill size, the time of day pills are taken, and the frequency with which the pillbox is refilled.

The IoT-based healthcare platform presented by G. Aquino et al. [135] (2021) to remotely monitor patients in critical conditions. Consequently, the aim is to develop the platform further by adding wearable and unobtrusive sensors to track the health of people who have contracted the coronavirus. They also detail the actual implementation of the method in a Brazilian critical care facility catering to patients with COVID-19.

Under the context of a telemedicine platform catering to the MENA area, H. Faris et al. [136] (2021) offered an intelligent diagnosis decision support system. The suggested solution uses the Altibbi company's massive health-related dataset, which contains various unstructured patient inquiries written in various Arabic dialects and organised symptoms reported by primary care physicians (GPs). The system incorporates a combination of machine learning models educated from two perspectives: the patient's symptoms and their medical inquiries.

Analysis of blood pressure, heart rate, and kidney function was proposed by Thilagavathy A. et al. [137] (2021). Glomerular Filtration Rate compares blood-stress levels to kidney characteristics (GFR). In theory, they suggest using a fuzzy logic system to represent the parameters; this system can also reason the risk to human health and conduct evaluations using rule-based criteria.

Patient satisfaction with telemedicine adoption in rural public hospitals in Bangladesh was studied by K M. Zobair et al. [138] (2021), who used the Expectation Disconfirmation Theory expanded by Social Cognitive Theory in their research. This study improves upon previous efforts by developing a theory-based prediction model for estimating patient satisfaction using telemedicine. A study model examines the role that patients' expectations, performance, disconfirmation, and enjoyment play in predicting their happiness with the use of telemedicine in Bangladesh. Both structural equation modelling and artificial neural network techniques are used in a two-stage validation process to ensure the accuracy of this model.

A novel crossover matching between machine learning techniques and the taxonomy of telemedicine was presented by Salman OH et al. [139] in 2021. The crossover taxonomy is created in the research to identify the connection between the machine learning algorithm and the comparable telemedicine classifications. The application of ML is most noticeable in the proposal of a hybrid synchronous/asynchronous telemedicine architecture.

The ECG intelligent health monitoring systems based on the IoT with machine and deep learning techniques are reviewed by J. N. Saeed et al. [140] (2021). To assist researchers in pushing the state of the art forward in future studies, the study also suggested avenues for investigation and new issues to tackle.

Recent advancements in medical imaging, medical video, and clinical deployment, enabled by contemporary computer vision algorithms driven by deep learning, are reviewed by Esteva et al. [141] (2021). They begin by providing a high-level overview of the last ten years of development in convolutional neural networks and the visual tasks they make possible in healthcare. Secondly, they outline several specific fields of medicine that might benefit from this type of imaging technology, such as cardiology, pathology, dermatology, and ophthalmology, and suggest future research directions. They go on to more broad areas of medical video, focusing on how incorporating computer vision into clinical operations might improve patient care. Lastly, they cover the difficulties inherent in using these technologies in clinical settings.

Mahboob Alam et al. [142] (2021) demonstrated how the Internet of Things (IoT) and fuzzy inference systems (FIS) can intelligently diagnose diseases. Fuzzy logic is the best way to handle ambiguity, making the Fuzzy System a potential medical diagnosing tool. They use sickness symptoms to identify new cases. Symptom-based diagnosis might be time-sensitive. IoT and FIS enable the proposed system to monitor symptoms and diagnose ailments. The diagnosed condition's severity was determined using many parameters. This study contrasts COVID-19, Typhoid, Malaria, and Pneumonia. This study used FIS to diagnose the illness by matching symptoms to data.

MATLAB runs the FIS. Due to the imprecise manner, symptoms might suggest affectionate sickness. Our investigation revealed that FIS could diagnose more diseases.

MT Qasim et al. [143] (2021) presented a Smart Healthcare Management Evaluation using a Fuzzy Decision-Making strategy to assess technology integration. This study evaluates the privacy protection an intelligent healthcare management system offers for patient information. This neural network predicts healthcare using fuzzy logic. The experiment measures fuzzy result precision, reliability, and mistake rate.

TrueImage is an automated picture evaluation machine learning pipeline proposed by K. Vodrahalli et al.[144] (2021) to identify low-quality dermatological images and assist patients in improving their photography skills. Notwithstanding the training data's variety and restrictions, our trials show that TrueImage can reject 50% of patients' low-quality photographs while preserving 80% of the high-quality images. These encouraging outcomes point to the viability of our technology and its potential to enhance teledermatology care.

Applications in automated seizure identification, prediction, and direction are highlighted in a study by Y Si et al. [145] (2021) that analyses several ML methods for electroencephalograph (EEG) signal procession in epilepsy research. The benefits, difficulties, and potential developments of ML approaches for EEG data processing in epilepsy are discussed in the present paper.

In order to categorise EEG data from epileptic patients, OK Cura et al. [146] (2020) employed a high-resolution time-frequency (TF) representation termed Synchrosqueezed Transform (SST). Seizure and baseline EEG data from 16 patients with epilepsy are used to generate SST matrices. The classification of seizure and pre-seizure signals is proposed using two methods based on ML and DL. The SST matrix was captured as a picture and then classified using a CNN-based architecture in the DL-based method. The results of the simulations show that both methods have reasonable validation accuracy rates. For the machine learning-based technique, they get a validation accuracy of 90.2%; for the deep learning-based procedure, they get a validation accuracy of 90.3 percent%.

MA Ozdemir et al. [147] (2021) suggested a unique technique for seizure detection and prediction using a high-resolution TF representation called the Fourier-based SST and a CNN. SST's TF plane signal component reassignment allows very localised TF energy distributions. SST accurately represents epileptic energy discharges on the TF plane. They evaluate the SST-based CNN technique using the publicly accessible CHB-MIT and proprietary IKCU datasets. Experimental results reveal high average segment-based seizure detection precision and accuracy across both datasets using the recommended technique.

SM Usman et al. [148] (2021) offered a successful preprocessing and feature extraction method. Their method increases the true positive rate and predicts epileptic episodes in advance. Pre-processed time and frequency domain data from empirical mode decomposition (EMD) was utilised to train a prediction model. The proposed model detects the preictal state.

The existing research on fog computing applications is surveyed by S Khan et al. [149] (2021) to uncover prevalent security holes. Including related technologies such as Edge computing, Cloudlets, and Micro-data centres provides a comprehensive look into the field. Functionality and user needs drive most Fog applications, while security is generally overlooked or treated as an afterthought. As a result of this paper's analysis, individuals responsible for building, developing, and maintaining Fog systems will better understand the future approaches that need to be taken to ensure the system's security.

Shi S. et al. [150] (2021), emphasising privacy and security, conducted a thorough literature evaluation of blockchain techniques for EHR systems. Before delving into the possible uses of blockchain in EHR systems,they provided a brief overview of the foundational knowledge between electronic health record (EHR) systems and blockchain. They also highlight several potential avenues for future study.

Using an anchor node, G. S. Walia et al. [151] (2022) found unknown nodes in 3D space. In this simulation, the middle and lower levels have moving nodes, but the top layer has a single anchor node. The Adaptive Plant Propagation Algorithm (APPA) is a new soft computing approach for locating these mobile nodes. The moving target nodes are heterogeneous and in an anisotropic environment with an irregularity of 0.01. Simulations show that APPA outperforms meta-heuristic optimisation techniques in localization error, computation time, and discovered sensor nodes.

In order to improve the accuracy, precision, training, and testing data capabilities of healthcare-related apps and frameworks, Sonali Vyas et al. [152] (2022) evaluate several works that use fuzzy logic systems and algorithms. Future studies should focus on increasing the reasoning component's flexibility by integrating new features into the existing cloud infrastructure and testing new machine-learning approaches.

Verma et al. [153] (2022) developed a cloud-based, IoT-based predictive technique for illness forecasting using data collected from biosensors to assess patient limitations. In addition to the regression method, they introduced a novel classifier called Generalized Fuzzy Intelligence-based Ant Lion Optimization (GFIbALO) for precise illness prediction. Before employing the proposed GFIbALO method for illness classification, the dataset undergoes filtering and feature extraction, following the regression rule for data processing. Assume further that some sickness has afflicted the patient; in this instance, the patient will be notified of the warning signal through SMS or other means. At this point, the patient can consult with physicians or seek other medical assistance. The MATLAB program is used to actualize the suggested GFIbALO classifier. The benefits of the suggested method in illness diagnosis and prognosis are then compared to those of the state-of-the-art procedures.

The purpose of the work by Shamsah Alotaibi et al. [154] (2022) is to provide a comprehensive overview of the methods used to identify seizures in children with epilepsy, with a focus on machine learning approaches and methods tested on the CHB-MIT scalp EEG database of epileptic paediatric signals.

HO Lekshmy et al. [155] (2022) need the ideal model to develop an ensemble model with improved learning capabilities. Classical machine learning methods like Logistic regression and the Naive Bayes model and deep learning methods like ANN, CNN, LSTM, and Autoencoders must be modelled and simulated. LSTM and Random Forest had the best sensitivity and specificity in this examination.

The suggested approach by P. Rajendran et al. [156] (2022) uses machine learning techniques to identify the onset of a seizure. The EEG records brain activity and can be used to diagnose seizures. KNN, ANN, SVM, and principal component analysis (PCA) are four machine learning classifiers that will be compared in this study for their respective levels of accuracy.

The classification accuracy of 99% was achieved by R M Khati et al. [157] (2022), a substantial improvement over the previous technique. Logistic regression with Adaboost had the best classification performance across ten cross-validation folds at 99% accuracy. Naive Bayes and Random Forest yielded an Area under the ROC curve of 1 for different reasons. The naive Bayes classifier yielded a perfect 100% sensitivity. For epilepsy detection, a convolutional neural network is used in conjunction with deep learning classification applied to EEG inputs. In addition, great classification accuracy may be accomplished with only a single-channel EEG, a new aspect of this method. Accuracy levels of 90% or more have been demonstrated numerically using a conventional test data set.

M H Aslam et al. [158] (2022) suggested a three-stage procedure framework. A PREP pipeline, a more complex replacement for simple notch filtering, is used to preprocess scalp EEG data. The SNR is improved using a regression-based technique, with both manually-created and automatically-created features used to predict seizures. Finally, interictal and preictal state segments are classified using LSTM. The proposed method achieves an accuracy of 94%, a specificity of 91.2% and a sensitivity of 93.8%. The suggested method outperforms the state-of-the-art approaches in terms of sensitivity and specificity.

X Cao et al. [159] (2022) proposed a domain-invariant deep feature representation strategy using adversarial learning to enable deep hybrid networks (HDN) to identify seizure types properly. The fine-tuned classifier determines the seizure cause. The experiments employed the CHB-MIT seizure database and TUH EEG Seizure Corpus. The domain adaptive deep feature representation improved deep hybrid model classification accuracy by 5% on the target set. It affects clinical EEG analysis using automated technologies.

The suggested approach by A. Pravin et al. [160] (2022) will be useful in identifying dengue patients early when therapy is more likely to be successful. The participants will be sorted into categories according to their symptoms, and an alarm will immediately be issued to their phones. The approach will aid physicians in determining the disease's impact through careful analysis of the results and prompt action within a constrained time frame.

An Internet of Things-based solution proposes [161] (2023) for home clinical settings to do remote monitoring and early identification of health concerns. The device can identify five types of heart rates.

We create an intelligent IoMT-based architecture for an E-healthcare patient monitoring system that employs AI algorithms [162] (2023). The Hybrid ResNet 18 and GoogleNet classifier (HRGC) predict abnormal/normal data. The next step is to decide whether to send a warning to hospitals and other medical facilities.

Smart healthcare delivery uses telemedicine, as described [163] (2023). This system also makes use of cutting-edge mobile technology. Artificial intelligence, machine learning, 5G and IoT platforms, and other supporting technologies have roles in the evolution of linked smart healthcare. It also highlights the difficulties and threats associated with providing such high-tech treatment to patients.

There was a presentation of a functioning prototype of a smart healthcare system [164] (2023) that would leverage the Internet of Things to provide high-quality healthcare available to everyone. They combined the ESP8266 microcontroller and the

ThingSpeak cloud with a remote temperature sensor during the development of this device.

2.2 Research Gap of Literature Review

Several studies have been carried out regarding telemedicine, fog which is discussed in Table 2.1

Table 2.1 Research Gap of Existing Work

Ref	Authors	Research Gaps
[91]	Kallipolitis, A. et al. (2020)	The technology is still in beta, and its accuracy is affected by lighting and where you place it.
[92]	Bulaghi, Zohre et al. (2020)	No thought is given to safety or energy efficiency.
[93]	Mani et al. (2020)	Inadequate safety
[94]	A. Abugabah et al. (2020)	Blockchain scalability becomes an important consideration, with a million healthcare transactions occurring every minute.
[95]	A. Banerjee et al. (2020)	The framework's flaw lies in its assumption that every patient receives care from a doctor or nurse, which is seldom the reality. Additionally, as the framework's development reaches its final stages, it becomes essential to conduct validation studies to test the hypothesis it relies on
[96]	I. A. Pap et al. (2020)	There is no thought to collecting data on various diseases, habits, or other

		physiological features because it would not create a superior learning set.
[97]	Zia et al. (2020)	There are no plans to create distinct application bundles for novice and advanced users or to incorporate other sensors, such as heart rate, electroencephalogram (EEG), or skin conductance, into the decision-making process.
[98]	J. M. Alvarez Q. et al. (2019)	Fuzzy Logic control methods have the drawback of being dependent on human experience and knowledge.
[50]	O. S. Albahri et al. (2019)	Ensuring the organization receives commercial and medical services, timely support to medical personnel, and delivering modern quality of life to indoor and outdoor patients are crucial.
[99]	A. Angelucci et al. (2020)	We need a better data acquisition system.
[51]	M. S. Ashapkina et al. (2019)	It is important to look for a range of motions.
[52]	M. N. Ashmawy et al. (2019)	powered by remote servers
[53]	Bilotta et al. (2019)	There is no explanation of how adding wearable sensors would enhance the system.
[54]	T. Buldakova et al. (2019)	Emphasizing safety rather than electricity and data transfer rates
[100]	A. Choi et al. (2020)	Users' physiological state must be tracked using a computer, smartphone, or other

		internet-connected personal device regardless of location or time.
[55]	Arun & Rad et al. (2018)	Since computing is expensive to implement,
[101]	M. Donati et al. (2020)	A system for intermediate-level analytics has to be implemented.
[56]	Y. Fan et al. (2019)	Selecting patients from various departments, categorizing vital signs for hierarchy analysis, measuring and evaluating WMD performance on an ongoing basis, and incorporating more sophisticated early warning systems all contribute to a more thorough monitoring strategy.
[57]	D. Ganesh et al. (2019)	Investigate calibration and precision.
[59]	E. Kaimakamis et al. (2019)	More work is needed on signal enhancement, integrated sensor miniaturization, and developing detection and DSS algorithms.
[61]	X. Li et al. (2019)	There is no study of latency or power use.
[62]	J. Liau et al. (2019)	Analysis of the sensor's accuracy is required.
[46]	W. Liu et al. (2018)	Patients need to be transferred to inter-service events as focal points, which may not happen if a provider is exclusively concerned with the patentability of its own devices.
[63]	Lopez et al. (2019)	Wearable sensors present significant challenges based on the prototype.

[64]	P. K. Maganti et al. (2019)	No attention is paid to the cloud's accuracy with respective parameters.
[103]	Mwaffaq & Otoum et al. (2020)	It is important to investigate several facets of illnesses.
[40]	D. Wu et al. (2016)	No thought is given to safety.
[66]	Md. Shahiduzzaman et al. (2019)	Not put through any real-world testing.
[67]	T. J. Swamy et al. (2019)	There is a lack of doctor-patient communication.
[68]	I. Wijesinghe et al. (2019)	Further work on image processing is required to boost the system's precision.
[87]	K. Zhang et al. (2020)	There is no investigation into efficient methods of storage and coordination.
[69]	X. Zhao et al. (2019)	There is a need to enhance the system's categorization accuracy for foetal movement signals.

2.3 Technology Comparative of Existing Work

Telemedicine systems are utilized for remote audio and video consultations, offering a cost-effective alternative to repeated hospital visits. Despite its value, telemedicine can pose affordability challenges for smaller healthcare facilities. To address this issue, introducing intelligent expertise systems at the intermediate fog layer can reduce costs and enhance reliability. Data quality remains a concern in healthcare-related projects. Given the global reach of IoT, leveraging IoT technology and interconnected healthcare data, along with Fog Computing services, can help alleviate the complexity of Big Data. The research inquiries have been developed through extensive literature surveys to incorporate new healthcare science technologies.

- How do IoT-driven healthcare systems ensure the safety and security of their operations?
- What is the necessity and functioning of a framework in healthcare?
- How does Fog Computing navigate the complexities associated with multidimensional ailments?

Table 2.2 Comparison of existing literature review over technology used

Ref	**Parameters/ Sensors Used**	**Objective / Methodology**	**Intelligence System**	**Layer Deployment**	**Remark**	**Alert**
[49]	blood pressure, heart rate, oxygen saturation, ECG, and temperature.	Fog computing, IoT, and machine learning are all used in this framework to give a better and smarter healthcare experience.	Yes (ML)	IoT, Fog, and Cloud	Used limited (two class classification) based on fixed health attribute	Yes
[50]	The NeuroSky Mindwave EEG headset, air flow, galvanic skin response, pulse oximeter, and temperature	an EEG-controlled device that would Interpret eye movement.	Yes (DL)	IoT, Cloud	Consider only EEG, Higher Computation requirement	No

[51]	Strip sensor	A ubiquitous central monitoring system for sleep and respiration	No	Cloud	Only used statistical calculati on	No
[63]	Heart rate, ECG, body weight, body temperature, oxygen saturation	For children with cardiac problems, a home telemonitoring device is being developed.	No	IoT, Cloud	Only used statistical calculati on	No
[64]	ECG, Temperature, GSR, PPG Sensor	A voice-controlled speech recognition system, a personal assistant	No	Bluetoot h	Only used regular rule-based system	No
[67]	respiratory and heart rate, SpO2, body posture, Lung Auscultation sounds, multi-lead ECG, and Electric	COPD patients with substantial comorbidities can benefit from an innovative telemonitoring solution.	No	IoT, Cloud	Only used regular rule-based system	Yes

	Impedance Tomography (EIT) imaging					
[72]	Wrist CK 1000 digital sphygmomanometer	E-Health System for Chronic-Hypertensive Patients' Arterial Pressure Monitoring, Transmission, and Storage	No	Wifi, Cloud	Only used statistical calculation	No
[78]	wearable cameras, accelerometers, gyroscope sensors	Smart Helmet Improves Fall Detection for the Elderly				
[79]	Temperature sensor, oxygen saturation (SpO2) sensor, Blood Pressure sensor	eSmart is a human-centric IoT-based intelligent health monitoring and management system.	Yes (DL)	IoT	Prototype modelling, No specific algorithm mentioned, the higher computat	No

					ion required	
[83]	Respiration, Body temperature, pulse, blood oxygen saturation, blood pressure, and electrocardiogram	a solution for a wireless telemedicine health monitoring system with many physical parameters	No	Cloud	Only used the regular rule-based system and statistical calculation	No
[84]	Accelerometer's sensor	Automatic monitoring of fetal movement.	Yes (ML)	Bluetooth, Cloud	System efficacy not given or poor, Lack of learning knowledge	Yes

These knowledge gaps have led to a novel computing and networking paradigm called Fog. Considering these factors, we propose an IoT-Fog-based healthcare framework for monitoring and predicting diseases at an early stage. Additionally, the system must provide real-time notifications to users and doctors during emergencies.

Figure 2.1 showcases the utilization of artificial intelligence (AI) across various aspects of telemedicine, specifically emphasising individual patient monitoring and diagnosis.

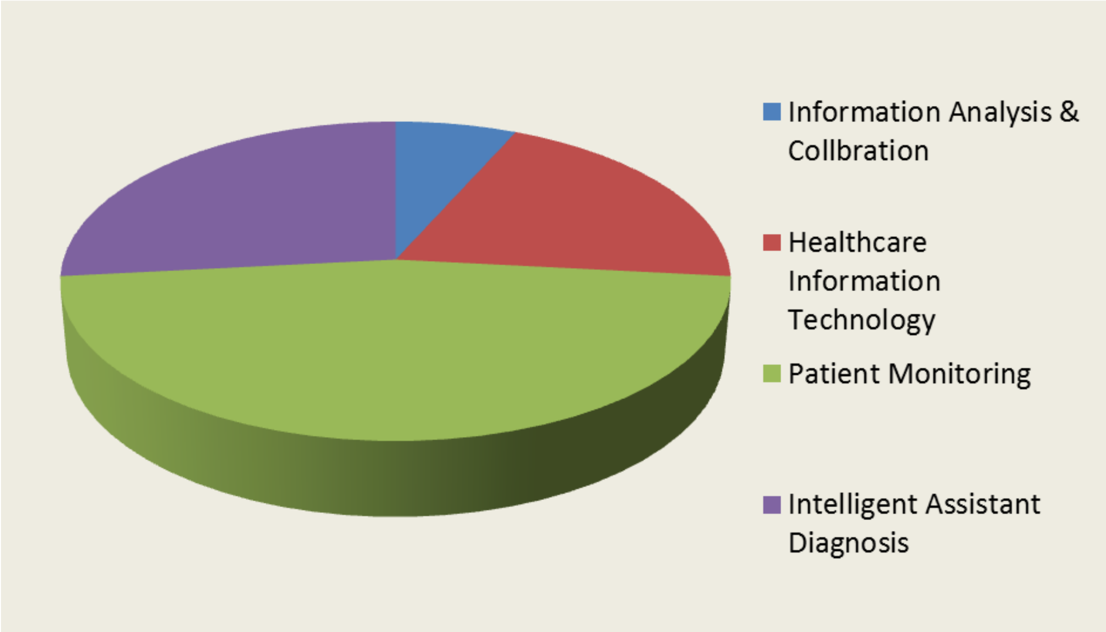


Figure 2.1 Utilization of AI in Various Areas of Telemedicine

Integrating patient monitoring and diagnosis within the framework of an e-healthcare system can significantly enhance its efficiency. This integration plays a crucial role in optimizing the impact of this technology and calls for further exploration.

Traditionally, cloud servers have been the primary choice for layer deployment in telemedicine implementations. However, it is essential to acknowledge the limitations associated with cloud-based solutions, including high latency, downtime, and security and privacy concerns. To overcome these challenges, the adoption of fog computing presents a promising alternative along with intelligent systems like ML DL.

CHAPTER 3 DEVELOPMENT OF THE INTERNET OF THINGS (IOT) ENABLED FOG COMPUTING ARCHITECTURE FOR REMOTE HEALTHCARE

3.1 Overview

The integration of IoT devices with advanced sensors and medical signal processing capabilities has a significant impact on enhancing comfort and convenience in people's lives. With the gradual increase in the number of patients, providing healthcare facilities to all individuals, especially those in remote areas, has become challenging, leading to various issues [2]. As a result, the development of smart healthcare systems has emerged as a vital research area to address these challenges. To overcome these issues, several healthcare applications have been designed using technologies such as Wireless Sensor Networks (WSNs), cloud computing, and fog computing [4-8] [10-12]. While cloud-based architectures are commonly used in e-healthcare applications, they introduce high latency when processing large volumes of data, limiting the widespread implementation of latency-sensitive healthcare solutions.

In contrast, fog computing architecture offers processing and storage resources closer to the network's edge, making it a promising approach for designing e-healthcare applications that require low latency. IoT-driven fog computing is being actively developed in the healthcare industry to expedite services for the general public and potentially save countless lives. Based on the fog computing paradigm, this innovative computing platform aims to reduce latency in transmitting and communicating signals with distant servers, enabling faster delivery of medical services in both spatial and temporal dimensions. The experimental solution relies on IoT device technology and embedded or wearable WBANs to realize Wireless Body Area Networks. In this architecture, WBSNs collect data and transmit it to a controller unit located at the Fog Layer, where it may be interpreted. These gadgets can be connected to the web and can be programmed. Again, unlike sensor networks, they are connected directly to the source of power and so have no energy constraints. Computing hardware and an expert, ingenious method is used for this purpose.

3.2 Proposed Framework

To realize WBANs, the proposed framework relies on the technologies of IoT devices and wearable sensors, as shown in Figure 3.1.

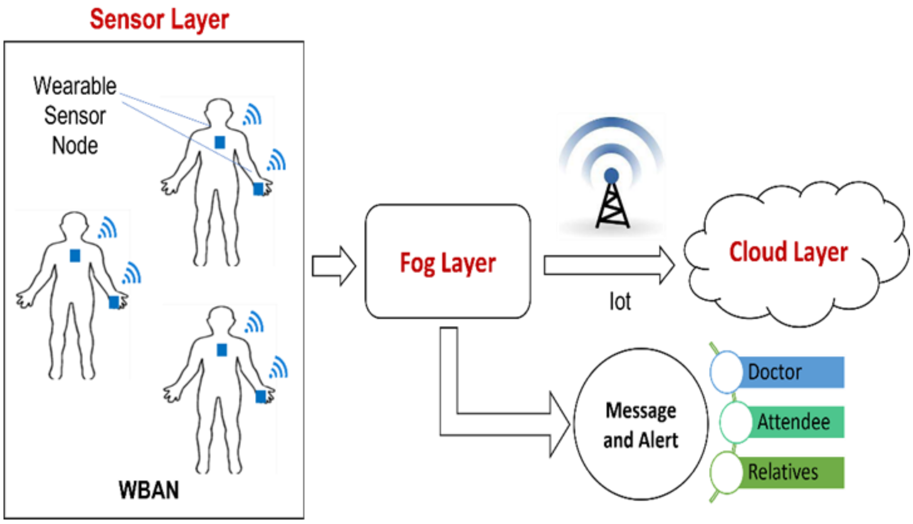


Figure 3.1 Proposed IoT-enabled Framework for Remote Health Care Services

3.2.1 Sensor Layer

The system includes wireless nodes that can be moved about and sensors that may be implanted or worn to keep tabs on your health. There are many different kinds of portable sensors available. Small wireless nodes in a WBAN talk to one another and monitor the human body and its environment with sensors and actuators. Information on a certain biological parameter is gathered by the nodes composing a Body Area Network from the human body and then sent to other nodes in the fog. The patient can go about his day, as usual, using wireless sensor nodes, all while being continuously watched. Zigbee and Bluetooth, two short-range wireless communication technologies operating in the license-free ISM band (2.4 GHz), are commonly used to implement WBAN [7-8]. It can also span huge distances using technologies like WiFi and the Internet of Things. These standard technological frameworks outline a procedure for deploying the necessary components of a network. However, there are alternative, non-standard, wireless communication methods that employ the same frequency spectrum to achieve the same results.

In our proposed experimentation, two nodes are used in sensor layers in which the Node MCU open-source platform is used, on which sensors for monitoring parameters including air quality, body acceleration, breathing sensor, heart rate, body temperature, and oxygen measurement in the blood are attached. The sensor nodes are attached to a shield that communicates with the microcontroller.

3.2.2 Fog Layer

The system's fog nodes process and analyse data, allowing for more accurate illness diagnosis and prognosis. Experts will guide the development of the analytics system that sends out alarm messages and collects data for the medical staff caring for the patient. The information collected by a sensor layer device is processed by fog computing, aggregating the resulting factors. It also distributes the data processing and administration tasks of the underlying network. Being the server that coordinates the work of several nodes in the fog, this layer is crucial. Data categorization allows us to utilize an analytics system to infer the value of a category variable from the value of a single other numerical or categorical variable.

The Fog layer provides authentication, processes the data provided by the IoT, and establishes a secure link to the cloud layer, all while acting as a high-computing connecting hub between the IoT and cloud levels [6] [12] [14]. Receiving credentials from the IoT devices, which are then checked against the Fog layer's primary database of users, is the first step in the authentication pipeline for admitting an IoT user in the Fog layer. Hypertext Transfer Protocol Secure (HTTPS) is used for all internal connections in the Fog layer to guarantee a safe authentication procedure. In addition, each user's record in the database will typically have the following key fields:

- Usernames and passwords are hashed before being kept.
- When users log onto the cloud, their information is encrypted using a 128-bit random identifying code.
- Encrypting data at rest in a cloud database requires an ID and a sub-key, both of which are assigned to data types inside categories.

After users have been authenticated, the Fog layer, which includes the following components, may provide them with the necessary security credentials to access their cloud-based data:

- The user identification code.
- The data type and its categories are associated with subKeys.

Two distinct types of user data may be defined by the context in which they are being used. The first group involves information that can be saved in its raw form without further processing, whereas the second group involves information that must be processed before storing it. Information often seen in medical records, including crucial information such as users' health sensed data, falls under the first group.

In our proposed experimentation, the analytics models are deployed on a fog layer in which an intelligent framework for illness detection is developed, which is a hybrid methodology termed "EMLR-FLIS" that combines Ensemble Machine Learning Regression (EMLR) with Fuzzy Logic Inference System (FLIS). The first step involves collecting health data from wearable sensors to use as benchmarks later for training and testing machine learning algorithms. The proposed experimentation uses two machine learning regressor models: ensemble bagging and ensemble boosting. After this, feature engineering is used to convert the raw data into sophisticated features, split into separate sets for use in the training and testing phases. Machine learning models are applied to the train feature set to generate a trained model after successfully validating the train model. After that, the output of the regressor-based machine learning model, which is the health score, is further given to the fuzzy inference system. The health score is initially used as a projected output in a fuzzy inference system to determine the patient's health status.

3.2.3 Cloud Layer

Our major goal is to investigate the Machine Learning-based recognition system and learn how it might help doctors better read vital signs and patient states. As part of the cloud, it stores information that may later be used to construct applications that provide real-time data to medical professionals, patients, or carers. The cloud layer is where information from the fog nodes is stored and managed before being used by a UI-driven app.

The proposed method accurately analyzed patient health data observed under several environmental conditions from sensors deployed in the sensor layer using an embedded system based on the MCU platform. All the measurements were tracked in real-time on a personal computer through serial transmission protocol. In addition, sensor data is published from the nodes to the Ubidots Cloud system [9].

3.3 Experimental Setup

The experimental setup in Figure 3.2 is used to verify the suggested framework stated above. The components of the suggested architectural framework are the sensor, fog, and cloud layer. The suggested experiment's Node 1 or Node 2 is the Node MCU open-source platform, on which sensors for monitoring parameters including air quality, body acceleration, breathing sensor, heart rate, body temperature, and oxygen measurement in the blood are attached. The sensor nodes are attached to a shield that communicates with the microcontroller. The Arduino IDE develops embedded C code for accessing sensor data. IEEE 802.11 wifi is used to transmit the data wirelessly. The coordinator's laptop computer is a wireless access point, connecting it to the Fog server. The coordinator sends information (sensor data) to the Fog server, where it may be processed. The sensor data is processed and stored in the fog server's database for analysis before it is sent to the Ubidots Cloud account through the MQTT protocol. A user interface (UI) dashboard can display information on a smartphone or tablet computer.

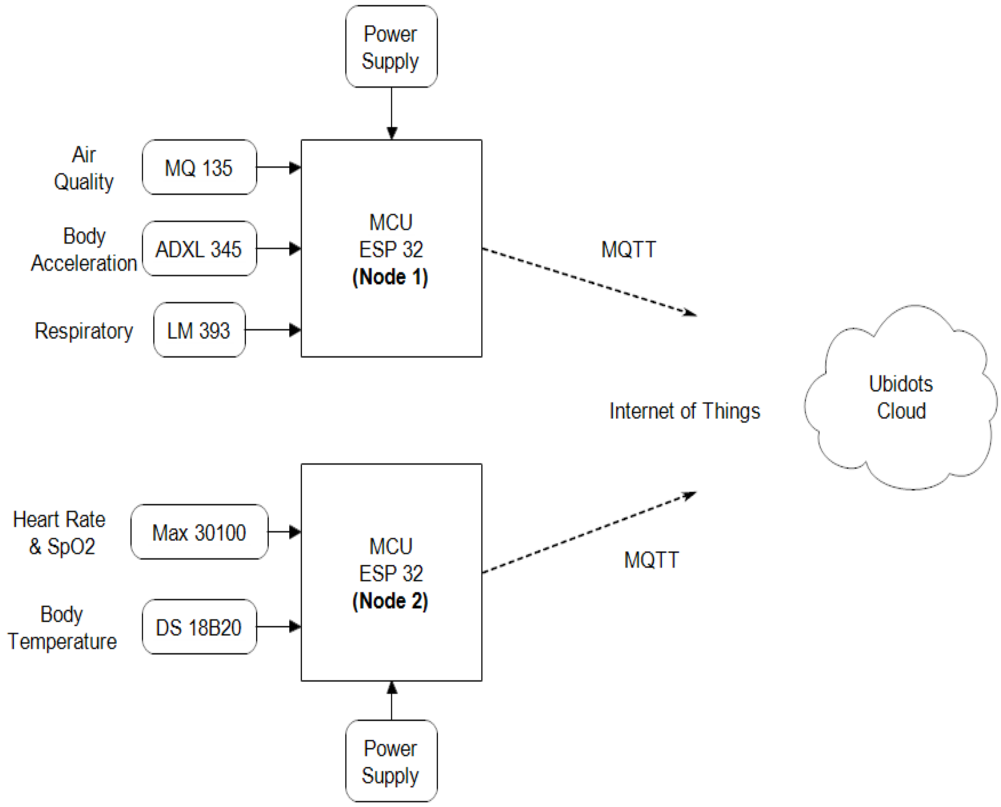


Figure 3.2 Proposed Experimental Setup

This experiment uses several sensors to measure various health parameters. MQ 135 is used to detect the presence of fresh air in terms of the air quality index of the surrounding environment. ADXL 345 sensor measures a person's posture, whether a sudden fall occurs in the patient's seizure or elderly patient. LM 293 sensor is used to detect the respiratory rate of a patient. Max 30100 sensor detects the heart rate and oxygen concentration in the patient's blood. DS 18b20 sensor is used to measure the body temperature of the patient. The Node MCU ESP 32 is the main heart of the system, which acts as a controller to which various sensors are interfaced. The data is sensed, processed, analysed, and monitored in real-time via serial monitor and over the Ubidots cloud service platform.

3.4 Flowchart of Proposed System

The operational workflow of the proposed system and how the procedure operates are defined in Figure 3.3. At the start, all sensors interfaced to the controller are powered on and initialized from Node MCU ESP 32 controllers. At an early stage, data from all sensors are acquired from the patient and monitored in real time. The all-necessary health parameters are checked and monitored for normal and abnormal events. All data is sent over Ubidots cloud by establishing an internet connection through nearby Wi-Fi services. The real-time data is visualized on Desktop or Mobile applications of cloud services. The data is uploaded on the Ubidots cloud server periodically over a certain period.

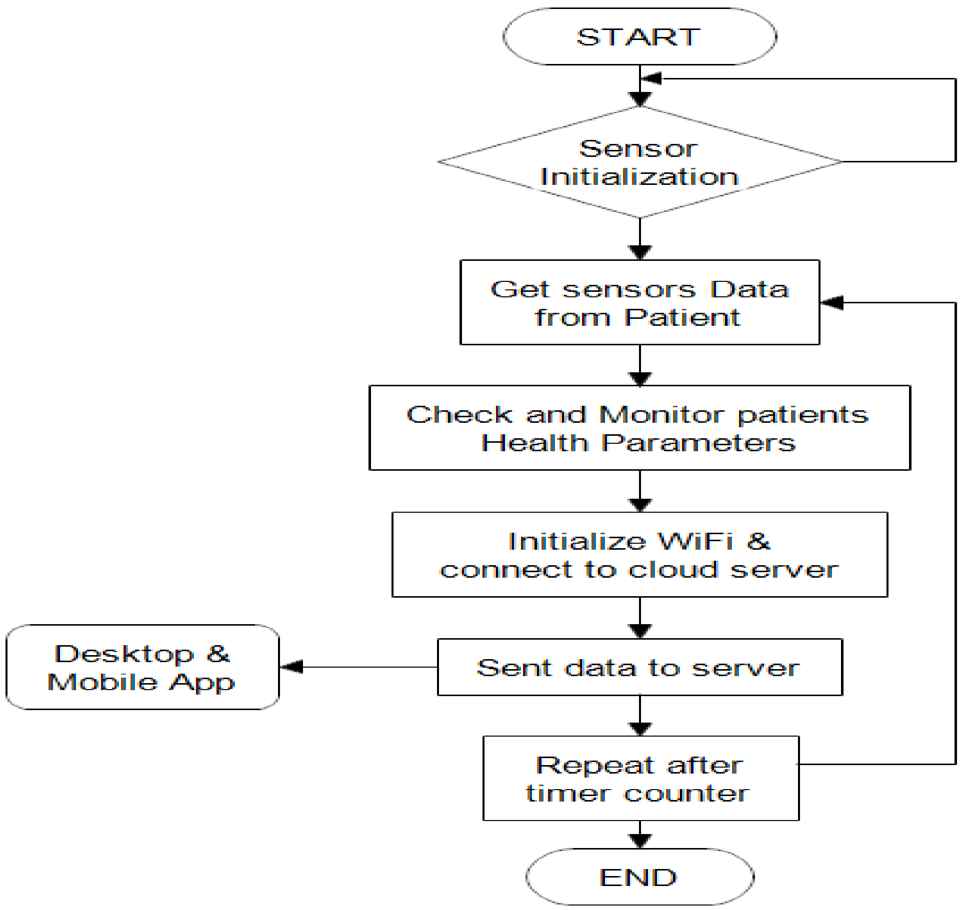


Figure 3.3 Flowchart of the proposed framework

The proposed system offers numerous significant contributions. It introduces a novel classification system for identifying epilepsy by leveraging regularly monitored health indicators of patients, primarily focusing on vital body parameters. To aid in decision-making for diagnosis, the system incorporates two modalities. It presents an enhanced diagnostic technique that combines machine learning and fuzzy logic, along with the innovative sensor data fusion approach.

3.5 Component Descriptions

The ESP32 microprocessor, at its heart, is responsible for all its connectivity features, including Wi-Fi, Bluetooth, Ethernet, and Low Power [41] [63]. The ESP32 incorporates a power amplifier, low-noise amplifiers, filters, and a power management module in addition to the antenna and RF balun. One of the development boards utilised and made for testing the ESP-WROOM-32 module is the Esp32 DevKit V1. In air quality control systems, the MQ-135 Gas sensors detect and quantify NH3, NOx, alcohol, benzene, smoke, and carbon monoxide. When only a single gas has to be detected, the MQ-135 sensor module's Digital Pin allows it to function independently of a microcontroller. The gases may be measured in parts per million by using the analogue pin. Complete with signal-conditioned voltage outputs, the ADXL335 is a small, low-power, three-axis accelerometer used to measure body acceleration.

Dynamic acceleration due to motion, shock, or vibration can be measured in addition to the static acceleration of gravity in tilt-sensing applications. The DS18B20 is a temperature sensor from maxim integrated used to measure the body temperature that can be programmed over a single wire. It is commonly utilised to measure temperatures in harsh conditions like chemical solutions, mines, dirt, etc. It measures temperatures from -55 to 125 degrees with an accuracy of plus or minus 5 degrees Celsius. The sound level sensor, used to measure respiratory rate, is measured via a microphone connected to an LM393 operational amplifier. There is a potentiometer on board for fine-tuning the volume. Sounds are picked up by the Sound sensor module's built-in microphone. The LM393 integrated circuit receives this signal. The MAX30100 is a versatile sensor used to measure heart rate and blood oxygen level with various possible uses. The sensor doubles as a pulse oximeter and a means of tracking heart rate. The sensor can measure heart rate and conduct pulse oximetry thanks to its two LEDs, photodetector, and low-noise signal processing modules.

The data is protected and kept confidential thanks to Message Queue Telemetry Transport's (MQTT) help. Lightweight publish-subscribe protocol that operates over TCP/IP; also known as MQTT [66-67] [69]. In MQTT, a message broker connects message senders with interested message receivers. The same client may be used to send and receive notifications. There is a topic that corresponds to each letter. The subject is the string containing the hierarchical tiers of the message's routing information, separated by slashes. The sending of data from a greenhouse's temperature sensors is seen in Figure 3.4.

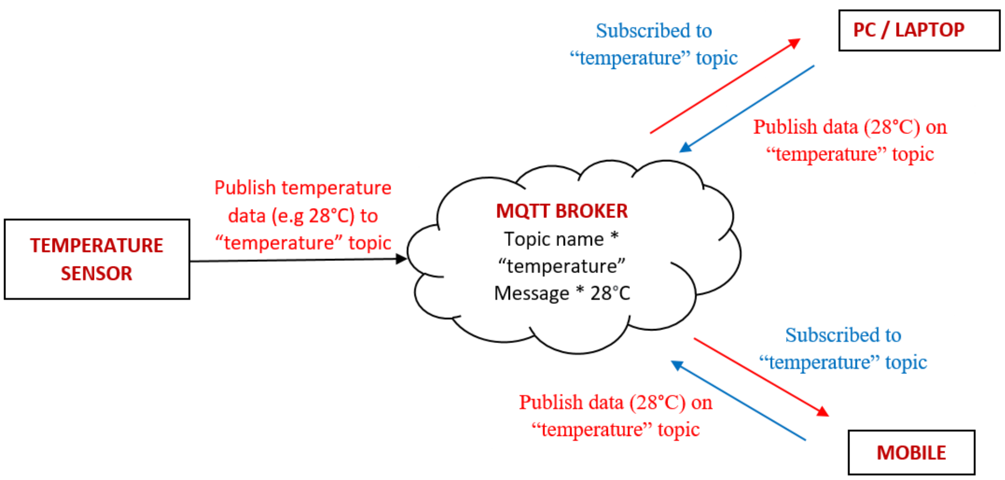


Figure 3.4 Workflow of MQTT for sensor data

By creating clients and brokers with the following core components, MQTT realises the publish/subscribe concept.

MQTT client

"MQTT client device" refers to any networked device capable of exchanging messages utilising the MQTT protocol. Every machine with the MQTT library installed, from a server to a microcontroller, is considered a MQTT client. The client is a publisher if it sends the message and a subscriber if it does the message.

MQTT broker

The MQTT broker is the backend system responsible for facilitating communication between clients. The broker is responsible for receiving and sorting messages, finding out which clients have subscribed to certain messages, and then sending those messages to those customers. It is also in charge of other things, including:

- Authorizing and authenticating MQTT clients
- Handling missed messages and client sessions
- Passing messages to other systems for further analysis

MQTT connection

An MQTT connection is established between the clients and the brokers. Clients send a CONNECT message to the MQTT broker to begin the connecting process. The CONNACK message is the broker's confirmation that the connection has been established. A TCP/IP stack is needed for communication between the MQTT client and the broker. The only person the client ever talks to is the broker.

3.6 Hardware Setup

As shown in Figure 3.5, a prototype was built using the suggested framework and tested with two nodes in various states representing their health parameters. Using an embedded system, the suggested method accurately analysed patient health data such as respiration rate, heart rate, blood oxygen level, and body acceleration. All the measurements were tracked in real-time on a personal computer through serial transmission and compared across various environmental conditions. In addition, by publishing data from the nodes to Ubidots broker, all of this sensor data could be watched over the Internet in a central location.

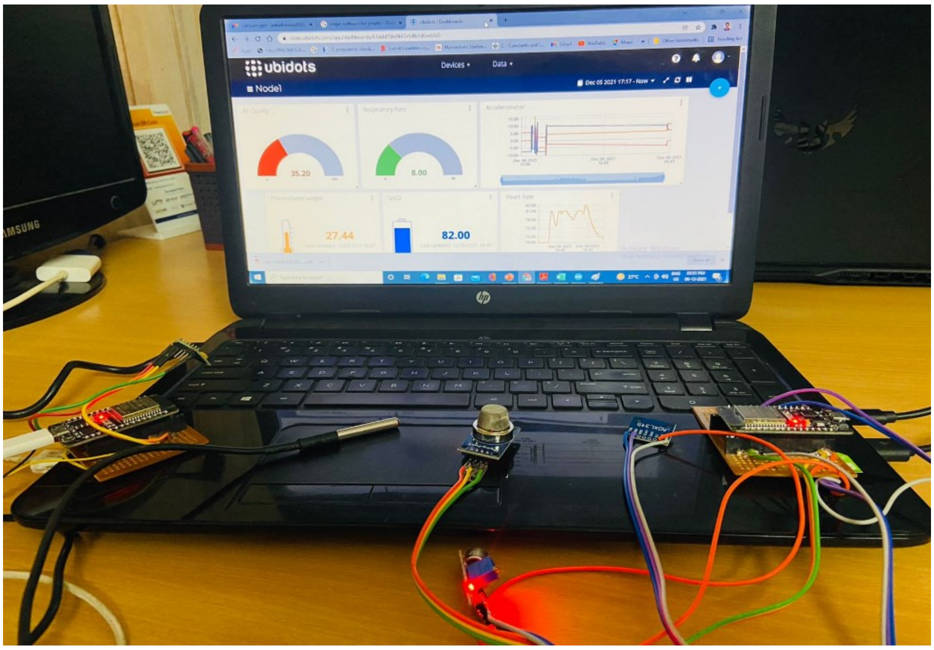


Figure 3.5 Hardware setup with two nodes implementation

The user might subscribe to these data and have instantaneous access, as shown in Figure 3.6.

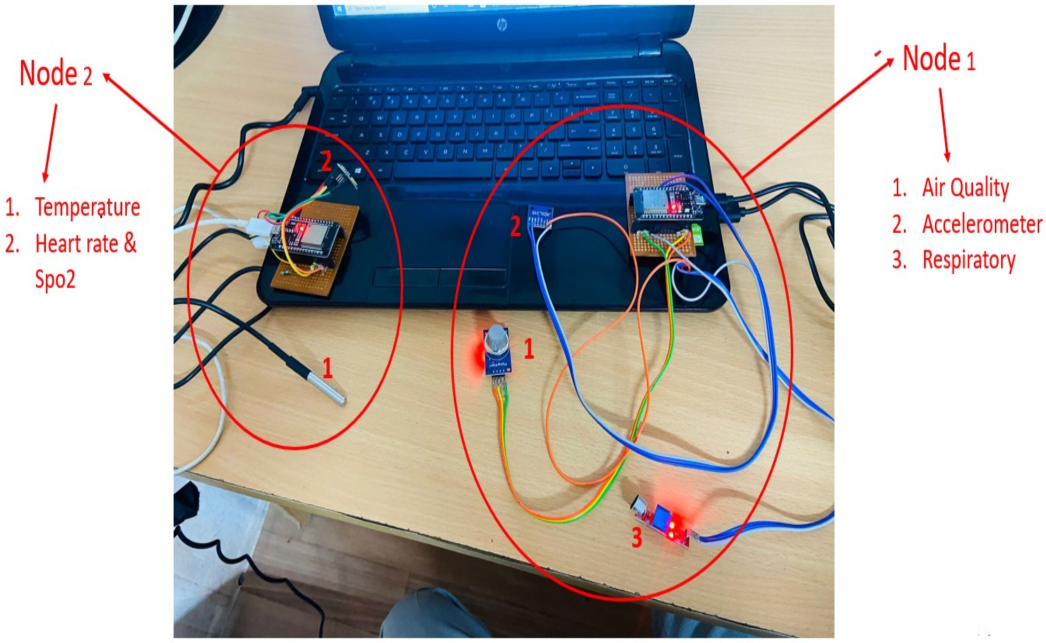


Figure 3.6 Hardware setup with real-time data visualization on Ubidots Cloud

3.7 Data Monitoring on Ubidots Cloud Platform

Ubidots is a business that specialises in data analytics and visualisation for the IoT. We process sensor data into actionable intelligence for commercial decision-making, machine-to-machine communication, academic study, and the conservation of world resources. Ubidots is an Internet of Things platform that helps businesses and startups bring their IoT ideas from prototype to mass production. Send information from any device with an Internet connection using the Ubidots platform.

The value of your data may then be unlocked using visual tools, such as the configuration of actions and alerts, depending on your real-time data. Ubidots provides a REST API for accessing and modifying its many data resources, including data sources, variables, values, events, and insights. An API Key is needed to access the API through HTTP or HTTPS. Two-way data replication, encrypted storage, and TLS/SSL data support are all in place to keep your information safe. Each platform module has its own set of permission controls, letting you choose which data is visible to which users. Ubidots are available so businesses and academic institutions may easily and affordably harness the potential of the IoT. Ubidots's technology and engineering stack was built to provide our customers with a private, personalised experience. Our cloud service's application programming interfaces (APIs) are designed to work with various devices and protocols, including HTTP, MQTT, TCP, and UDP. Ubidots' time-series backend services are second to none when storing, processing, and retrieving IoT data. We have an IoT App Builder that lets programmers add their own HTML/JS code for private customisation, and we offer real-time, interactive data visualisation (widgets) on our application enablement platform. Ubidots is a service that facilitates data transfer from any given source to any desired display format. Figure 3.7 displays, from the server of the Ubidots cloud platform, real-time information gathered by the experimental setup.

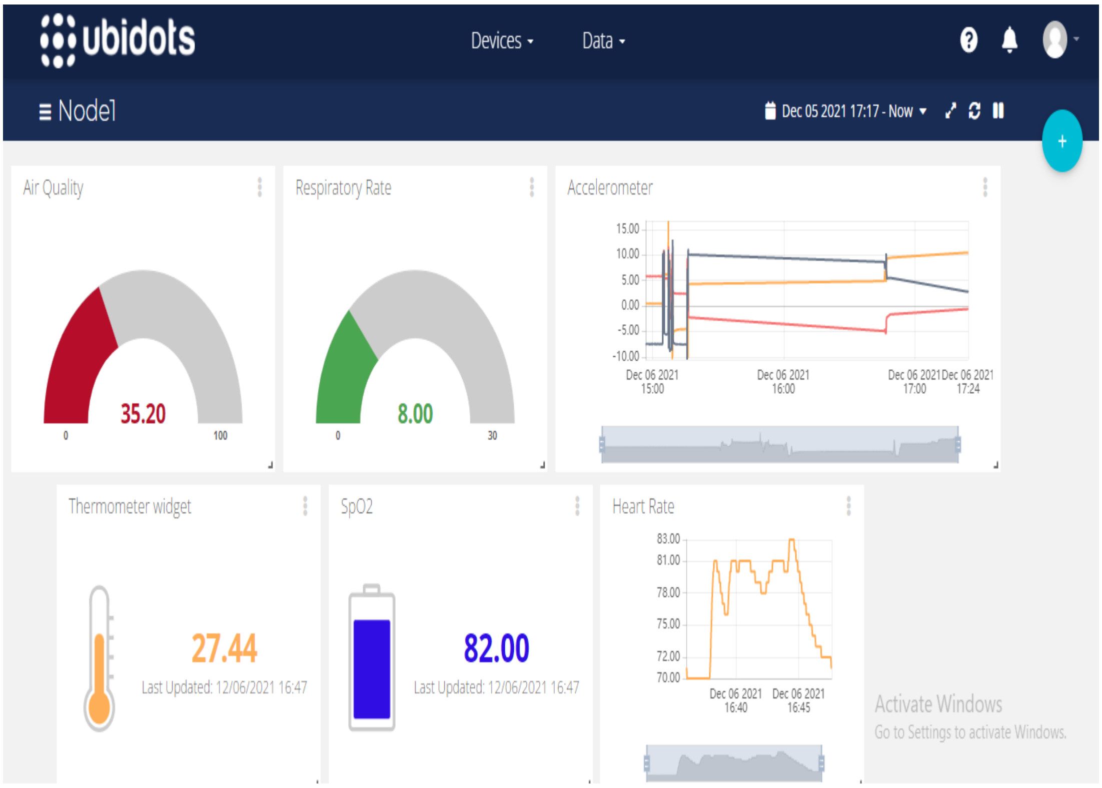


Figure 3.7 Real-time data observations of prototype model on Ubidots Cloud Platform

3.8 Data Interpretation

Wearable sensor parameters are monitored, reflected upon, and examined to ascertain the system's potential use in various human undertakings. The cloud displays the statistical data distributions for two sensor nodes linked to healthy persons for each sensor parameter. If any readings are beyond the specified range, an alarm will be generated for the doctor or caretaker.

Extracted from the prototype device in real-time over 30 events with a 1-second interval for five categories based on the age group. Considered age group for the observation has been taken as 0-5 years, 5-10 years, 10-30 years, 30-60 years and 60+ years.

Figure 3.8 shows the respiratory rate of various categories to understand how the rate has varied according to age group. It has been observed that a healthy individual has a respiratory rate of 16–20 breaths per minute, whereas a sick person has a rate higher than this.

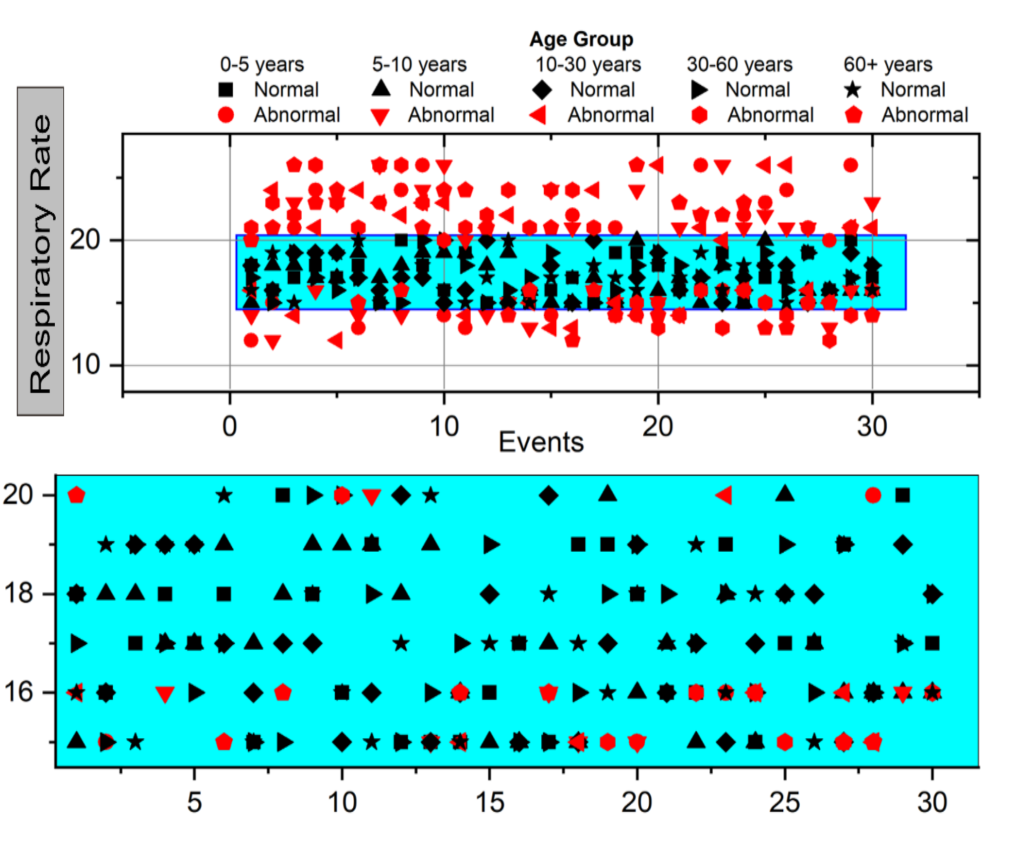


Figure 3.8 Data Interpreted for Respiratory Rate

Figure 3.9 displays the body temp of various categories to understand how the rate has varied according to age group. The average normal range for a human body temperature is 36.5 to 38.5 degrees Celsius.

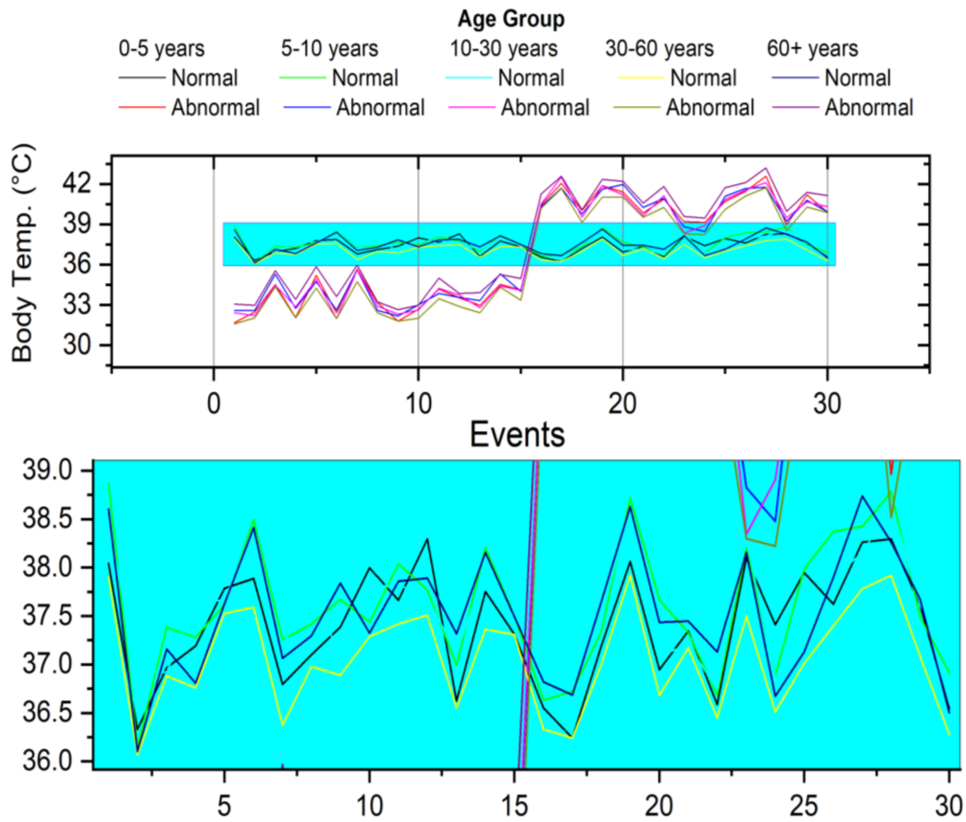


Figure 3.9 Data Interpreted for body temperature

Figure 3.10 displays the heart rate of various categories according to age group, and it has been observed that the average normal range for a human heart rate is 60 to 100 beats per minute.

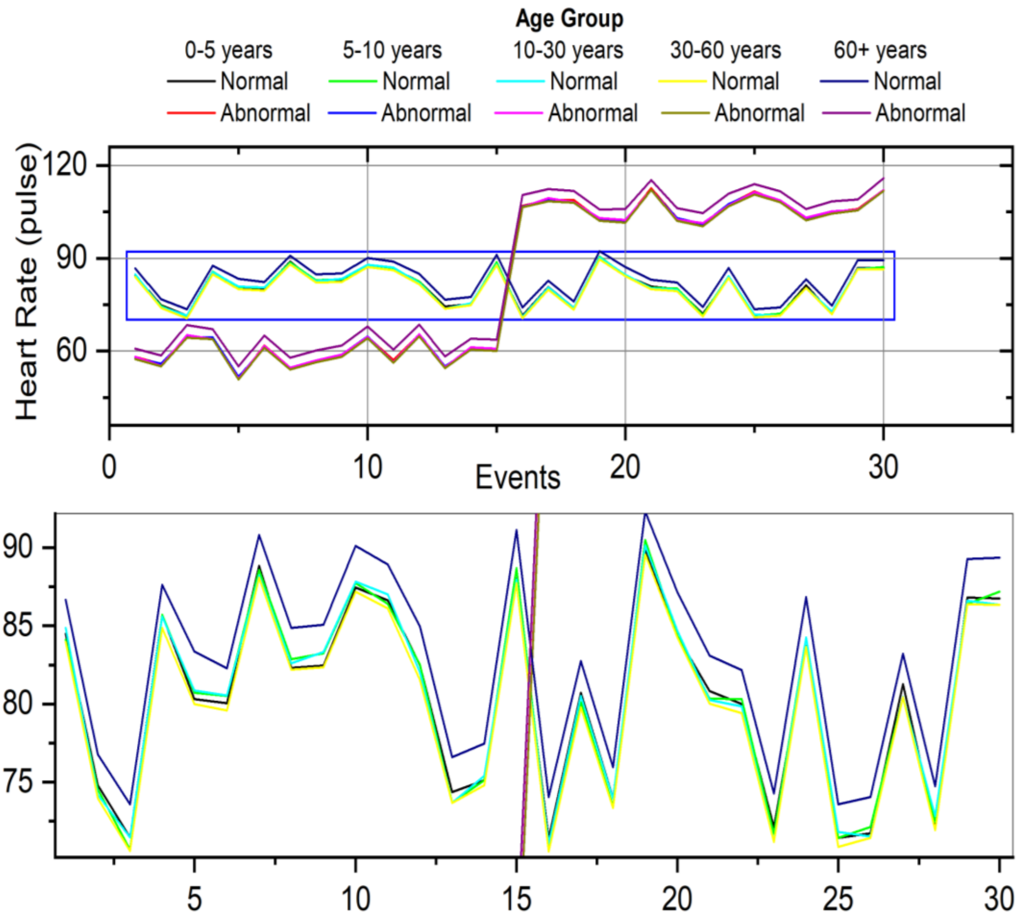


Figure 3.10 Data Interpreted for Heart Rate

Figure 3.11 displays SpO2 of various categories to understand the normal range of SpO2 according to age group. The normal range for human oxygen saturation (SpO2) is over 95%.

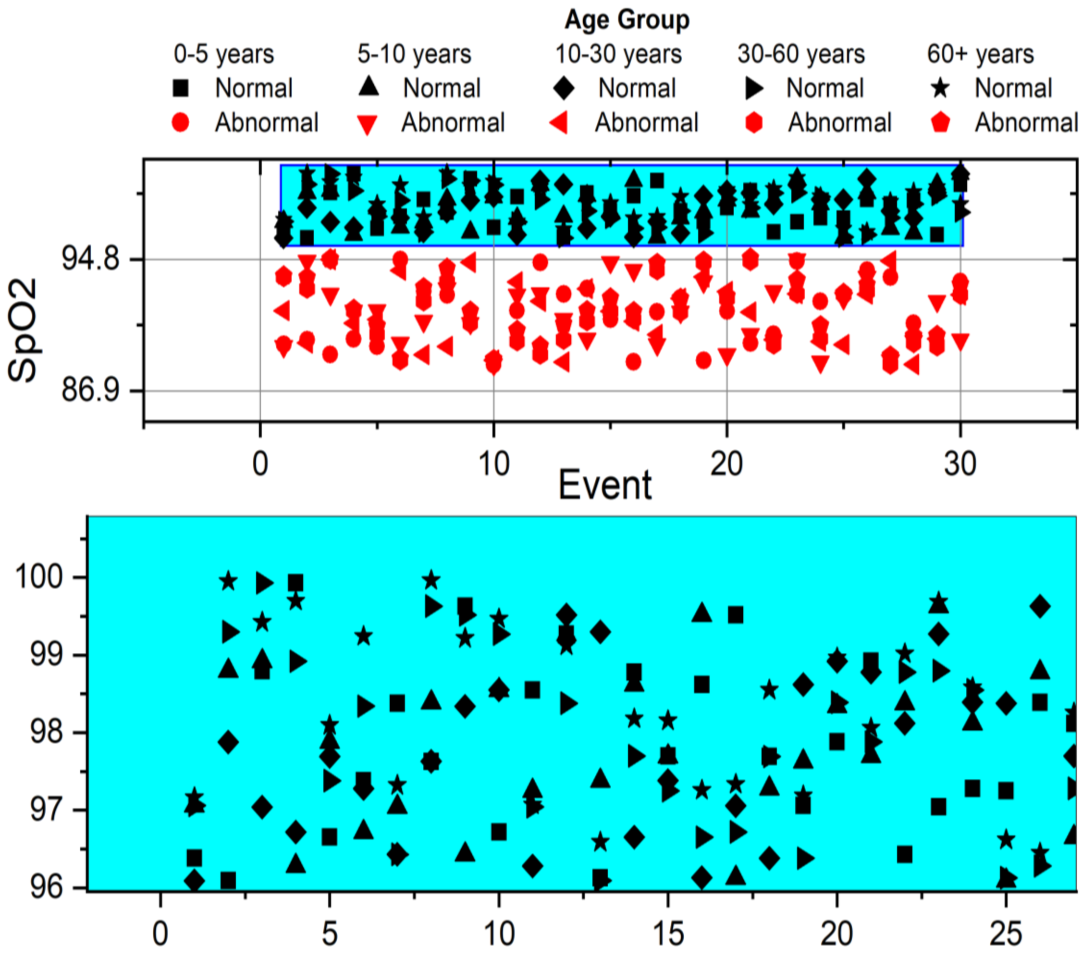


Figure 3.11 Data Interpreted for Body SpO2

Figure 3.12 displays air quality checks for different conditions. The air quality index was assessed to make the false case assessment, and it was determined to be below 100 PPM, the threshold at which pollutants become harmful to human health.

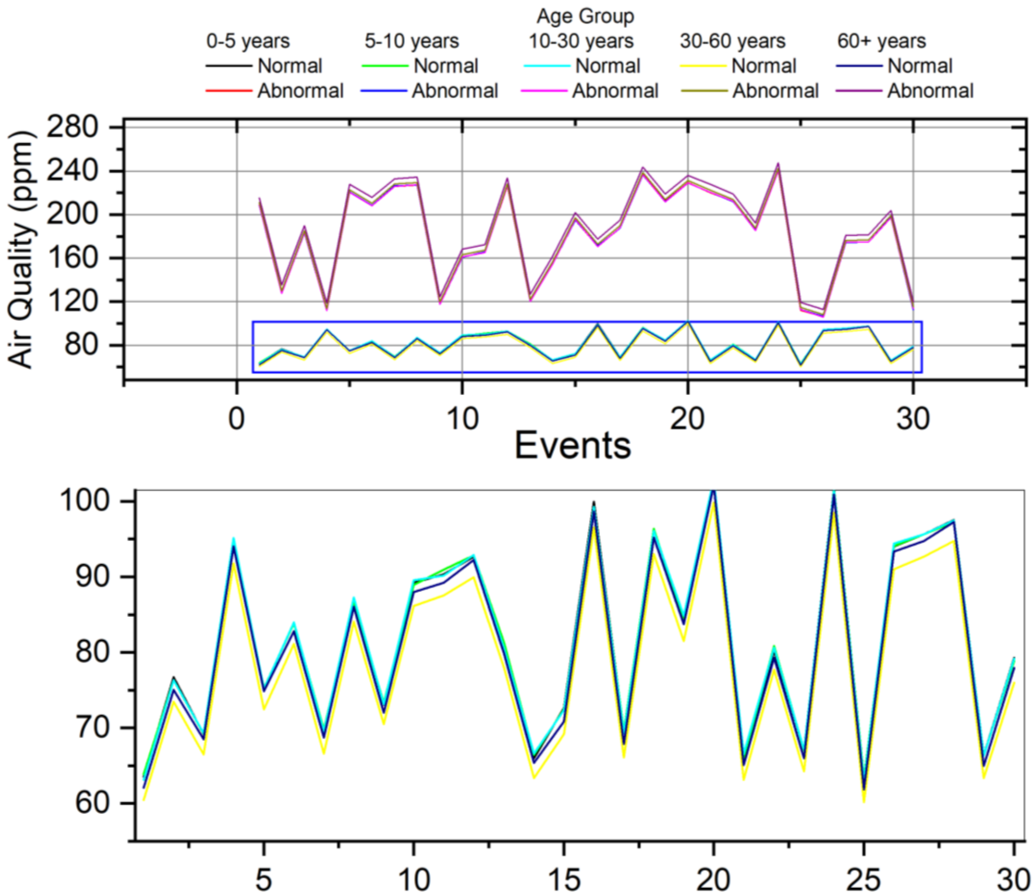


Figure 3.12 Data Interpreted for Air Quality

When a person's measured value falls outside of a predetermined range, called a threshold, an alarm signal is created and forwarded to the appropriate medical professional, patient, or carer, following the priority assigned to each.

Figure 3.13 displays each user's average respiratory rate, body temperature, air quality, SpO2, and heart rate in various test conditions. The final average range for different categories based on age groups for various sensors has been evaluated after interpreting data shown in the figure below:

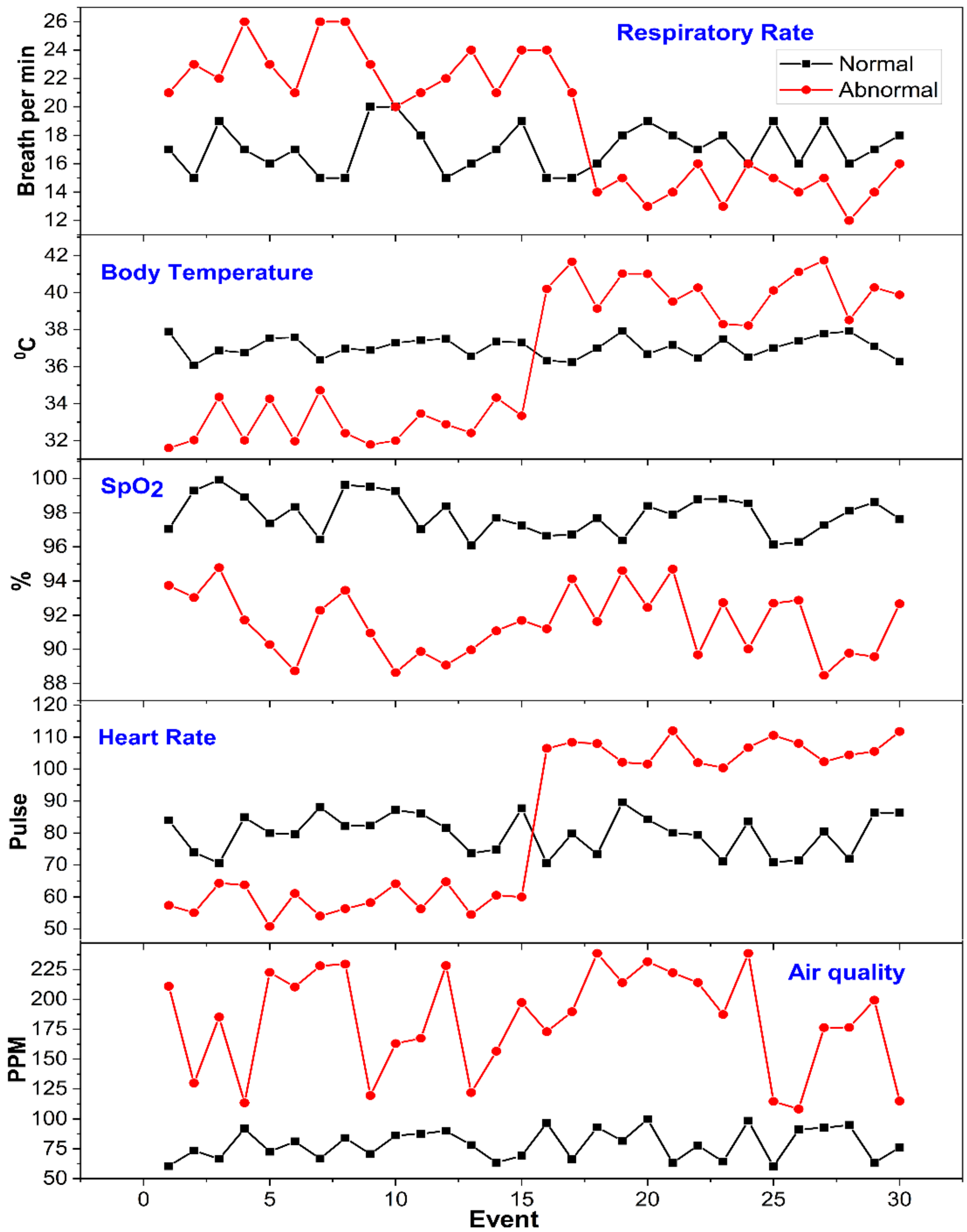


Figure 3.13 Data displaying the average normal range for various sensor parameters

3.9 Summary

This chapter presents the proposed IoT-based framework based on Fog Computing for Remote Health Care Services with an effective and reliable data monitoring system, which mainly consists of a primary three-layer architecture: sensor layer, fog layer, and cloud layer. The main objective of this framework is to develop a prototype system considering two nodes for monitoring the patient's health parameters under several circumstances for disease diagnosis over a cloud server platform. In the proposed experimentation, monitor the behaviour of patients using various sensors for different health parameters on a cloud server and visualize the data on the IoT cloud platform using MQTT protocol with its data interpretation.

CHAPTER 4 DEVELOPMENT OF INTELLIGENT FRAMEWORK FOR DISEASE DIAGNOSIS USING MACHINE LEARNING DEPLOYED AT FOG LAYER

4.1 Overview

This section discusses the proposed method for deploying an intelligent framework for illness detection using the Fog Layer, which is a hybrid methodology termed "EMLR-FLIS" that combines Ensemble Machine Learning Regression (EMLR) with Fuzzy Logic Inference System (FLIS). The first step involves collecting health data from wearable sensors to use as benchmarks later for training and testing machine learning algorithms. After this, feature engineering is used to convert the raw data into sophisticated features, split into separate sets for use in the training and testing phases. Machine learning models are applied to the train feature set to generate a trained model. The health score is initially used as a projected output in a fuzzy inference system to determine the patient's health status.

4.2 Hybrid Framework Using EMLR-FLIS

The proposed block diagram of an Ensemble Machine Learning Regression-based framework with a Fuzzy Logic Inference System (EMLR-FLIS) is shown in Fig 4.1 below.

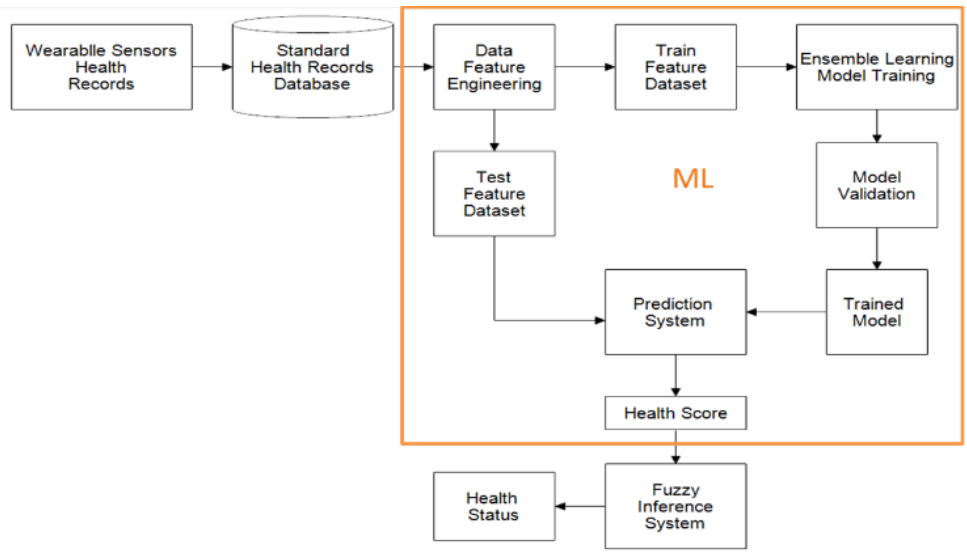


Figure 4.1 Proposed Block Diagram of Hybrid Framework

4.2.1 Clinical Records Dataset

Table 4.1 details the health characteristics of the dataset, which consists of conventional clinical records taking the health behavior of patients with epilepsy into account. Professionals supervise the process of acquiring and analyzing this dataset. In the table, the readings of a hundred volunteers' health sensors are recorded while they track their activities during specific times of the day while living in a simulated environment to generate the suggested data. Using an IoT-based cloud service platform, researchers analyze data from one hundred participants to determine the daily mean value of their experiments.

Table 4.1 Health Attributes for Epilepsy Patients

Input	**Output**	**Measurement Unit**
Air quality	Health Score (Regression-based value)	Parts per million (PPM)
Body acceleration		Three-axis motion records
Respiratory rate		Breath per min
Heartbeat rate		Beats per minute (BPM).
Oxygen level in blood		Percentage (%)
Body Temperature		Degree Celsius (°C)

4.2.2 Feature Engineering

Using data mining tools, feature engineering extracts features from unstructured data. Algorithms for machine learning can perform better when given access to these features. One may classify feature engineering as machine learning in an application. Additionally, it converts unstructured data into attributes that the predictive models can use to understand the underlying issue better, enhancing model accuracy for previously unknown data.

Two objectives are the main focuses of feature engineering:

- An appropriate input dataset that meets the requirements of the machine learning method.
- Enhancing the effectiveness of machine learning models.

The accuracy of classification or estimation performed by intelligent algorithms is enhanced by pre-processing the data, such as resampling, normalization, noise filtering, attribute selection, etc. The dataset feature samples are initially subjected to standard scaling with normalization.

4.2.3 Ensemble Machine Learning Regression (EMLR)

Exploring the connection between a set of characteristics or independent variables and a result (the dependent variable) is the goal of the regression-based classification method. In machine learning, this technique is used for making forecasts. For instance, "how comfortable a person is" is defined by an algorithm used to forecast continuous outcomes for health data categorization using a health score. Machine learning regression techniques include Random Forest Classifier, and Ada boost Classifier.

The analytics platform based on regression analysis looks at how different factors affect one another. The purpose of ensemble learning, a meta-method, is to improve classification performance by combining the predictions of many models. The health score measures "how comfortable a person is following epilepsy," the approach is part of machine learning's predictive modelling process by which an algorithm predicts continuous outcomes for the classification of health data.

The suggested method makes use of the ensemble learning regression model, which makes use of both ensemble bagging and boosting. Many decision model trees are mapped to different subsets of the dataset, and then the average predictions from each tree are used in the Bagging approach. Boosting adds ensemble members consecutively that correct the forecasts supplied by prior models, yielding a weighted average of the projections. Bagging makes use of the random forest bagger regressor. Boosting makes use of the Adaboost regressor. The results of a regressor trained using machine learning are sorted into epilepsy severity levels ranging from 0 to 1.

Random Decision Forest (RDF) uses ensemble learning to aggregate multiple weak classifiers to offer solutions to challenging issues. An algorithm for supervised learning is a random forest. The "bagging" method's "forest" is constructed from several decision trees. The bagging method is based on combining learning models to improve the model's final output. Generally speaking, a forest seems more vigorous the more trees there are.

A random forest, as the name suggests, is made up of several decision trees. However, instead of relying solely on one tree, it uses the predictions from each tree to forecast the ultimate result based on most predictions. Similarly, with the random forest classifier algorithm, the more decision trees there are in the forest, the more accurate the model is.

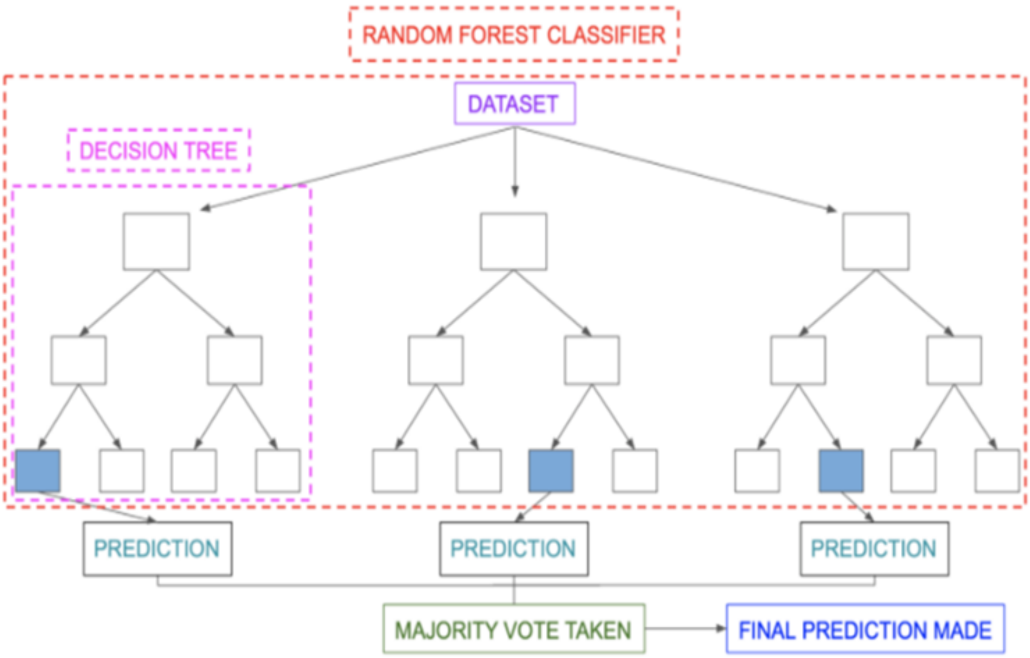


Figure 4.2 Learning Process of Random Decision Forest

Figure 4.2 illustrates the division of the data into training and testing halves. Random forest is then applied to the training portions. Based on our training data, the random forest generates several decision trees, which accurately predict outcomes when tested. The vast majority of data points in the output are used to calculate it. It increases the model's accuracy because of this.

Step 1: Create subsets of our original data. Row and feature sampling refers to choosing rows and columns with replacements and producing subsets of the training dataset.

Step 2: Build separate decision trees for each subset. Use a random selection of k features from m features in the training data such that k m to construct a decision tree that links the sample data points together.

Step 3: Each tree of decisions will provide a result. Determines the best possible feature selection for a split of k.

Step 4: The node should be cut into offspring using the best possible split.

Step 5: Carry on until you reach the leaf node.

Step 6: Continue doing this until you have a thick forest. Finally, find the predictions made by each decision tree for the most recent data points and assign those to the most popular class. If B is bagging, classification trees might make predictions based on the majority vote.

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \qquad \text{Equation 4.1}$$

Step 7: The final result is evaluated using the majority voting method when solving a classification or regression problem.

The behavioural logic of the random forest algorithm is defined as follows.

To make *n* classifiers:
For *i = 1* to *do n*
Sample the training data *T* randomly with a replacement for *Ti* output
Build a *Ti* - containing root node, *Ni*
Call *BuildTree (Ni)*
end For
BuildTree(N):
If *N* includes instances of only one class, then it returns
else
Select *z%* of the possible splitting characteristics at random in *N*
Select the feature *F* with the highest information gain to split on
Create *f* child nodes of *N, Ni ,..., Nf,* where *F* has *f* possible values *(F1, ... , Ff)*

For $i = 1$ to f do
Set the contents of *Ni* to *Ti*, where *Ti* is all instances in *N* that match *Fi*
Call *Buildtree (Ni)*
end for
end if

The AdaBoost (AdB) algorithm, also known as Adaptive Boosting, is a boosting approach used as an Ensemble Method in machine learning. For each new instance, weights are recalculated to increase the penalties for incorrectly labelled cases, thus called "adaptive boosting." Boosting is used to reduce bias and variance in supervised learning. It has based on the idea that learning happens in increments. All subsequent students are created from existing ones except for the initial learner. These pupils go from being weak to becoming powerful. In order to generate a robust learner, the boosting method combines several weaker learners. Each model performs adequately on a limited portion of the data but fails when applied to the whole set. As a result, adding more models boosts the overall performance.

Step 1: Create the dataset from scratch and give each data point the same weight. Initialize the dataset and provide each data point with the same weight. The initial weighting can be determined by,

$$w(x_i, y_i) = \frac{1}{N}, \; i = 1, 2, \ldots n \qquad \text{Equation 4.2}$$

Where N indicates the total number of data points and the number of records.

Step 2: To find the data points incorrectly categorized, provide this as input to the model. Give the model this as input and see the data points incorrectly categorized. The actual influence is categorizable using

$$\alpha_t = \frac{1}{2} ln \frac{(1 - TotalError)}{TotalError} \qquad \text{Equation 4.3}$$

Where Alpha indicates the weight that each stump had in the final judgment, the total error is the number of misclassified data.

Step 3: Boost the significance of the data items that were incorrectly categorized. Incorrectly classified data points should have more weight, whereas correctly classified data points should have less weight. Then, adjust all data points' weights to their original values. To update the sample weights, the following formulae are used.

$$\omega_i = \omega_{i-1} * e^{\pm a} \qquad \text{Equation 4.4}$$

Here, multiplying Euler's number by the previous sample weight yields the new sample weight. If the records are accurately categorized, Alpha will be positive; otherwise, it will be negative.

Step4: if (results are satisfactory)

goto step 5

else

goto step 2

end

Step 5: Predictions are formed using a new model based on the dataset.

Step 6: Many models are developed similarly, each fixing the flaws of the previous model.

Step 7: The weighted mean of every model (weak learners) makes up the final (strong learners) model.

4.2.4 Fuzzy Logic Inference System (FLIS)

Singleton output membership functions that are constant or linear in the input values are used in Takagi-Sugeno-Kang fuzzy inference, also known as Sugeno fuzzy inference. Instead of computing the centroid of a two-dimensional region, the defuzzification technique for a Sugeno system uses a weighted average or sum of a limited number of data points, making it more computationally efficient than the corresponding procedure for a Mamdani system. A fuzzy inference system interprets a health score as an input by assigning values to the output vector based on normal, severe, and critical health conditions. Any statement's truth becomes a matter of degree in fuzzy logic. The principle of the proposed FLIS appears in Figure 4.3.

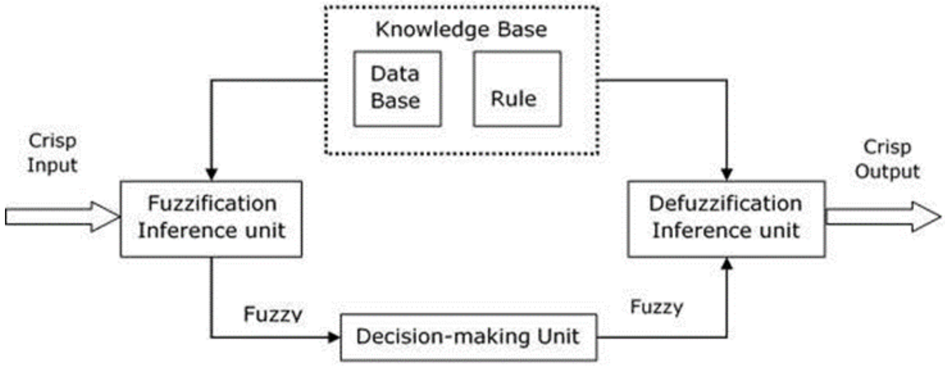


Figure 4.3 Principle of FLIS

The following five functional blocks define the construction of FLIS.

- Fuzzification Interface Unit: This unit transforms precise values into fuzzy values.
- Database: It defines the membership functions of fuzzy sets utilized in fuzzy rules.
- Rule Base: It comprises fuzzy IF-THEN rules.
- Decision-making Unit: This unit executes operations on the rules.
- Defuzzification Interface Unit: This unit converts fuzzy values into precise values.

The Fuzzy Inference System (FIS) functions through the following process:

- Using diverse fuzzification techniques, a fuzzification unit converts the crisp input into fuzzy input.
- After converting crisp input to fuzzy input, a knowledge base is constructed, consisting of rule bases and databases.

- The fuzzy output from the defuzzification unit is ultimately transformed into crisp output. The fuzzification unit transforms the crisp input into fuzzy input and supports using various fuzzification techniques.

4.2.4.1 Fuzzy Inference Data for Health Parameters

Tables 4.2 to 4.6 depict the fuzzy variable relationship between input and output with their respective ranges for health parameters like body temperature, heart rate, oxygen level in the blood, respiratory rate, and acceleration rate. All input defines the symptoms based on sensor reading values, and output defines the status of health conditions from HS0 to HS3 of health parameters. For acceleration data, health position is defined as HP1-HP3 as fall, normal, sitting [165-168].

Table 4.2 Body Temperature Data

Input Membership Function Variable	Ranges (deg cel)	Output Membership Function Variable	Ranges
Hypothermia	< 36	HS-1 (Health Score)	0-0.3
Normal	36 - 37.5	HS 0	0.25-0.6
Light Fever	37.5 – 38	HS +1	0.5-0.7
Moderate Fever	38.1 - 38.5	HS+2	0.6-0.8
High Fever	38.6 - 39.5	HS+3	0.7-0.9
Very High Fever	39.6 - 42.5	HS+4	0.8-1.0

Table 4.3 Heart Rate Data

Input Membership Function Variable	Ranges (beats per minute)	Output Membership Function Variable	Ranges
Bradycardia	< 60	HS-1	0-0.4
Normal	60-100	HS0	0.3-0.7
Tachycardia	>100	HS+1	0.6-1.0

Table 4.4 Oxygen Level in Blood Data

Input Membership Function Variable	Ranges (%)	Output Membership Function Variable	Ranges
Normal	95-100	HS0	0-0.3
Mild Hypoxemia	91-94	HS+1	0.2-0.55
Moderate Hypoxemia	86-90	HS+2	0.5-0.8
Severely Hypoxemia	<85	HS+3	0.7-1.0

Table 4.5 Respiratory Rate Data

Input Membership Function Variable	Ranges (breaths per minute)	Output Membership Function Variable	Ranges
Bradypnoea	<12	HS-1	0-0.4
Normal	12-20	HS0	0.3-0.7
Tachypnoea	>20	HS+1	0.6-1.0

Table 4.6 Acceleration Rate Data

Input Membership Function Variable	Ranges (g)	Output Membership Function Variable	Ranges
Standing	1	HP1 (Health Position)	0-0.3
Sitting	2	HP2	0.2-0.55
Squatting	3	HP3	0.5-0.8
Lying	4	HP4	0.7-1.0

4.3 Algorithm Steps

INPUT Standard benchmark dataset form sensor containing Health Parameter Dataset with features and labels
OUTPUT

Predicted disease diagnosis health score class.

Pi - Classes: [0 - 1]

PROCEDURE

Feature Engineering

Step1: Determine the size of feature data and target data, Fz, and Tz

Step2: For in range of Fz

Apply scaler transformation to each sample

Data normalization with equal distribution for each class end

Step 3: Make ready the MLR parameters

Epochs/Neurons/Performance Parameters/Training Algo/Data Division

Make ready MLR with training and target Data

Extract Features layers from the network

Predict the model with train data to get feature data

Classification

Step 4: Initialize Parameters for training MLR Models

Step 5: Find hyperparameters of the trained model using Grid Search Optimization

Step 6: Train the model based on best-selected hyperparameters

Step 7: Validate the model by getting a training loss minimum

Step 8: Store the trained model in the knowledge repository

Testing

Step 9: Load user test data

Step 10: Apply feature engineering from steps 1 to 3

Step 11: Load the trained model from step 8

Step 12: Predict the health score of health parameter data to get a precise health score.

Step 13: Define linguistic variables and terms used to describe health metrics.

Step 14: Construct the membership function for the linguistic variables.

Step 15: Built the knowledge rule base

Step 16: Fuzzification: Perform fuzzification by converting crisp facts to fuzzy values using the membership function.

Step 17: Inference Engine: Utilize the inference engine to analyse the rule in the rule base

Step 18: Inference Engine: Combine the result of each rule in the inference engine.

Step 19: Defuzzification: To convert output data into non-fuzzy values, perform defuzzification.

4.4 Summary

This chapter develops an intelligent framework for disease diagnosis using a hybrid approach with the help of a ML Algorithm and a FLIS. In the proposed experimentation, health parameters records are considered for Epilepsy patients. Initially, a regression-based machine learning algorithm is used to build the intelligent model, which predicts the data as the severity of epilepsy. Further, this severity is classified into disease types as per fuzzy knowledge defined for it. There are two algorithms, ensemble bagging and boosting, used for learning. Ultimately, the performance of the proposed system is thoroughly analysed and validated.

CHAPTER 5 EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Experimental Setup

The proposed experimental setup uses PyCharm 3.11.1 software with Anaconda distribution to implement the system. Medical professionals watch over system testing. Using the suggested device, samples are obtained from various situations. First, sensor-based data was transmitted to the server. This dataset was gathered and examined with the assistance of professionals. The data that is being proposed is a compilation of health sensor readings from 100 participants who participated in simulated daily life for a specified amount of time. A data logger on an IoT-based cloud service platform is used to analyse the mean value of experimentation over a dataset of 100 individuals for a single day. Both the Arduino app and a web browser show the findings. After receiving data gathered by sensors and transmitted through a smart device, the server generates a sample of the patient's report. The report is divided into three sections: sensor data, patient data, and patient symptoms, measured by health scores. The suggested method is a low-cost and effective option for residents of remote locations; they may use it to determine whether they have a significant health problem and, if so, seek appropriate treatment by contacting regional hospitals. In telemedicine, a novel concept is using sensors and decision support systems. Using analytics, medical facilities may achieve greater accuracy, early disease diagnosis, personalization, and cost savings.

5.2 Performance Parameters

The classification efficiency measures from a confusion matrix that provides the result of counting correctly and incorrectly identified cases by event class (normal/abnormal). Therefore, some statistically defined measurements are considered and used for the comparative analysis of classifiers. The metrics were evaluated for several performance measures applied to determine the quality of a chosen classifier for the needs of this research: Accuracy, Specificity, Sensitivity, F-score, Negative Predictive Value (NPV), Positive Predictive Value (PPV), False Negative Rate (FNR), and False Positive Rate (FPR) were evaluated.

The classification efficiency measure is derived from the confusion matrix, which provides information on the number of correctly and incorrectly classified cases based on event type (normal vs. abnormal). In order to conduct a comparative analysis of classifiers, multiple statistics-based measurements are taken into account. The evaluation of a classifier's performance includes various performance metrics such as RMSE, accuracy, precision, recall, f-score, sensitivity, specificity, True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), and Receiver Operating Characteristic (ROC). Also root mean square error (RMSE) is evaluated. N is no. observation taken.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad \text{Equation 5.1}$$

$$Precision = TP / (TP + FP) \quad \text{Equation 5.2}$$

$$Recall / Sensitivity = TP / (TP + FN) \quad \text{Equation 5.3}$$

$$Specificity = TN / (TN + FP) \quad \text{Equation 5.4}$$

$$F - score = 2 * TP / (2TP + FP + FN) \quad \text{Equation 5.5}$$

$$Negative\ Predictive\ Value\ (NPV) = TN / (TN + FN) \quad \text{Equation 5.6}$$

$$False\ Positive\ Rate\ (FPR) = FP / (FP + TN) \quad \text{Equation 5.7}$$

$$False\ Negative\ Rate\ (FNR) = FN / (FN + TP) \quad \text{Equation 5.8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}} \quad \text{Equation 5.9}$$

5.3 Performance of the EMLR-FLIS Model

By analysing the statistical health record histogram plot, as depicted in Figure 5.1, researchers can gain valuable insights into the distribution of the dataset. The histogram plot visually represents the frequencies or counts of events within specific values. The horizontal axis of the plot corresponds to the range of values, while the vertical axis represents the frequency or count of events falling within the range or value T. The height of each bar in the histogram corresponds to the number of occurrences or data points within that particular range of values.

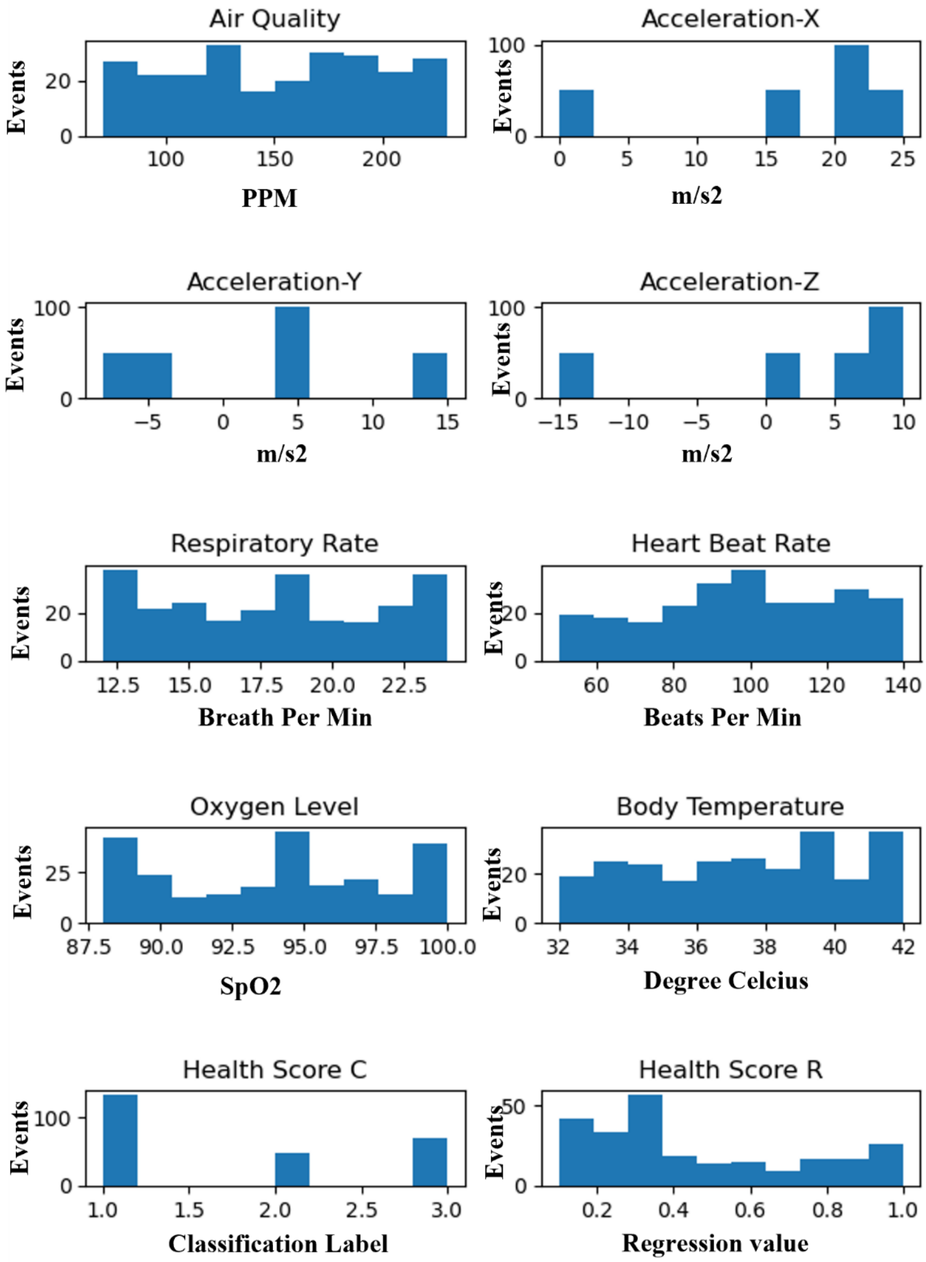


Figure 5.1 Output Label Data Histogram

Utilizing PyCharm, the histogram plot offers a powerful tool for comprehending the distribution and characteristics of the dataset in a research context. The plot specifically incorporates input parameters like air quality, acceleration-x, acceleration-y, acceleration-z, respiratory rate, heartbeat rate, oxygen level, body temperature, health score C and Health score R. The x-axis showcases the range or values of the input parameter, while the y-axis indicates the frequency of each parameter.

Overall, the histogram plot generated by PyCharm provides valuable insights into the distribution of medical data, allowing healthcare professionals and researchers to understand the prevalence and characteristics of specific medical measurements or variables within the dataset. It helps identify trends, potential outliers, and patterns essential for making informed medical decisions and conducting further analysis.

It serves as a crucial component in research analysis, highlighting the relationship between input and output parameters in the context of health records.Furthermore, the health score output classification data was visualized using histograms, where health scores of 1, 2, and 3 were classified as normal, mild, and severe, respectively. These classifications are depicted in Figure 5.2. Most of the output classifications fell into the normal category, accounting for 54.44%. The remaining output categories, mild and severe, represented 19.35% and 26.21%, respectively.

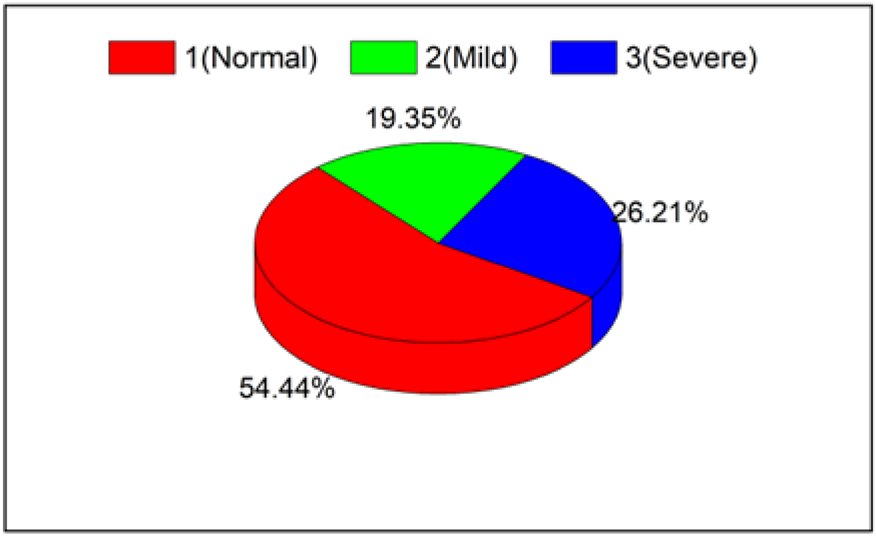


Figure 5.2 Count of label data

The correlation matrix between the variables shown in Figure 5.3, generated by PyCharm, provides a valuable tool for analyzing the relationships between variables within a dataset.

Each cell denotes the correlation coefficient between two variables within the correlation matrix. The correlation coefficient is a statistical indicator that measures the strength and direction of the linear relationship between the variables. Its value can range from -1 to 1, where -1 signifies a complete negative correlation, 1 represents a complete positive correlation, and 0 signifies no correlation between the variables.

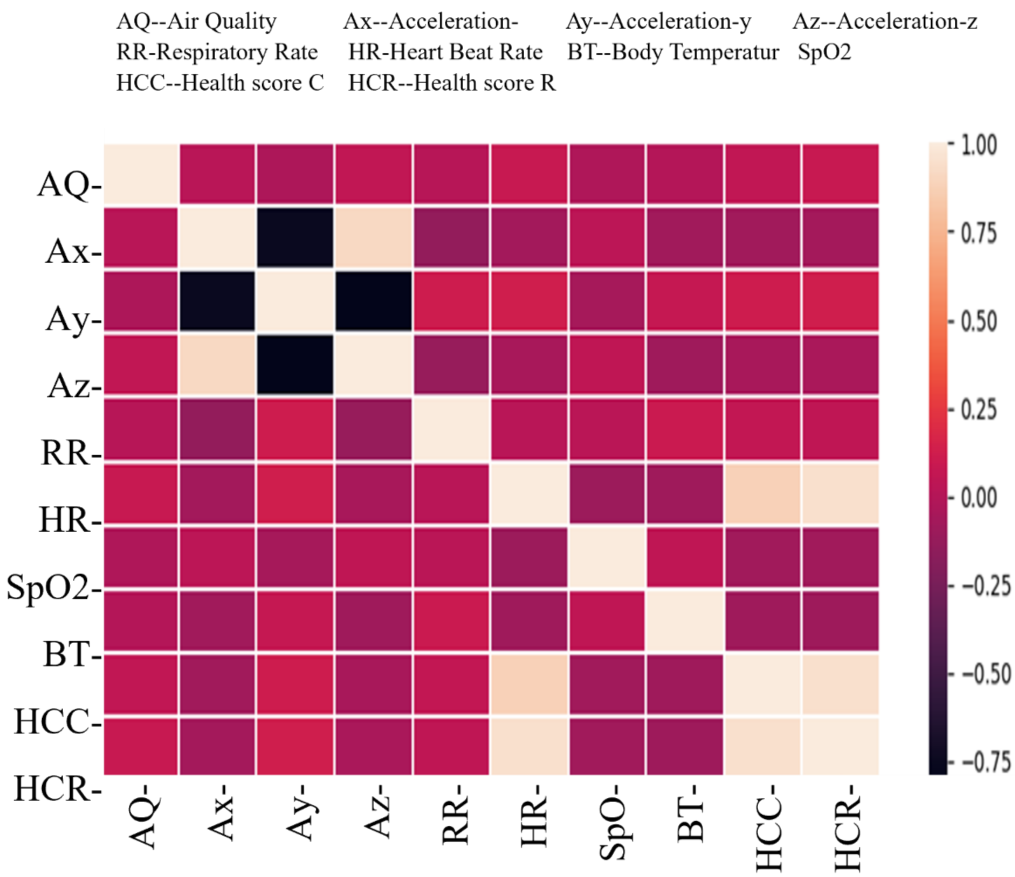


Figure 5.3 Correlation Matrix of Input Variable Data

The correlation matrix is represented visually through a color distribution bar, depicting the relationships between different attributes. Bright colors in the matrix indicate strong relationships, while darker colors signify weakly or no relationships between the attributes.

The simulated result for ensemble regression-based algorithms with bagging is shown in (Annexure-I).

Figure 5.4 compares the predicted and actual Output nature, employing a bagging regressor. This comparison is a valuable measure to evaluate the performance and accuracy of a predictive model. In the proposed work, the bagging algorithm, an ensemble regression-based approach, is trained and validated following a specific procedure. The predicted values, highlighted in red, demonstrate a close alignment with the actual values represented in green. This strong alignment signifies that the model performs well and can accurately predict the target variable with a training accuracy of 99%.

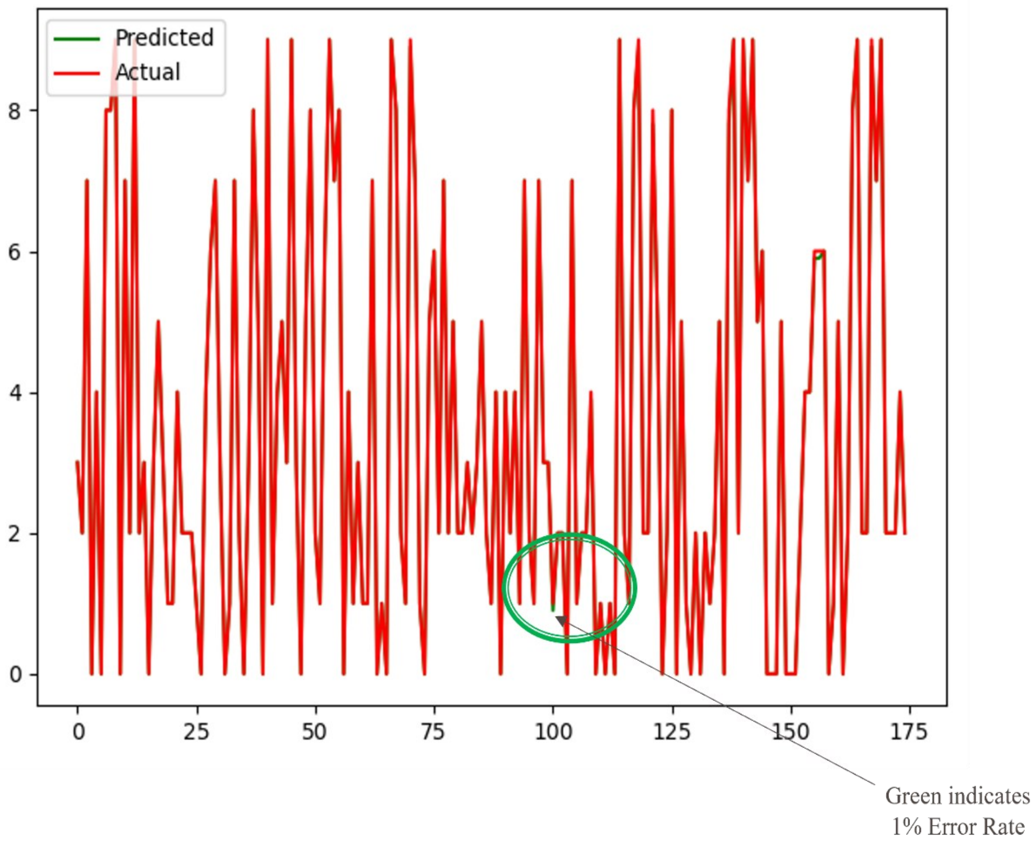


Figure 5.4 Predicted vs. Actual Output Nature using Bagging Regressor.

The simulated result for ensemble regression-based algorithms with boosting is shown in Annexure II. In the initial stage, the boosting algorithm is trained and validated according to the procedure described in the proposed work. A comparison between the actual and predicted output nature is plotted in Figure 5.5 to assess the algorithm's performance. Upon analysis, it is examined that the algorithm accurately predicts the exact data with an impressive training accuracy of 100%.

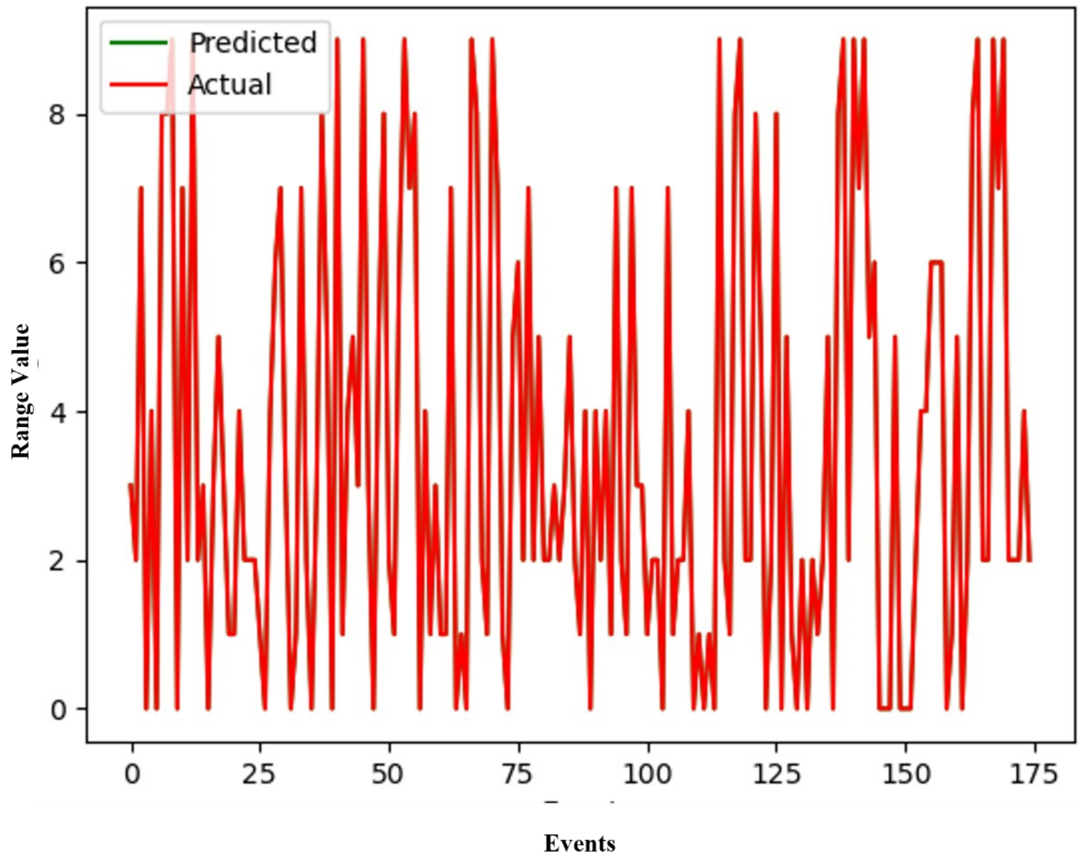


Figure 5.5 Predicted vs. Actual Output Nature using Boosting Regressor.

Later, performance was evaluated, analysed and compared for both algorithms. The results indicated that the proposed system demonstrated the capability to predict data compared to the ground truth data accurately. The ensemble boosting algorithm demonstrates superior performance with a score of 100%, surpassing the bagging algorithm in terms of the effectiveness of training the models.

The research includes an investigation of root mean squared error and accuracy for two algorithms, presented in Table 5.1.

Table 5.1 Performance of Regressor Algorithm

Parameters	Ensemble Bagging	Ensemble Boosting
RMSE	0.02	0.01
Accuracy	0.98	0.99

Additionally, Figure 5.6 graphically represents the performance comparison between the ensemble boosting and bagging algorithms. The results indicate that the ensemble boosting algorithm outperforms the bagging algorithm, achieving a higher score of 0.99 in terms of performance of testing the proposed models.

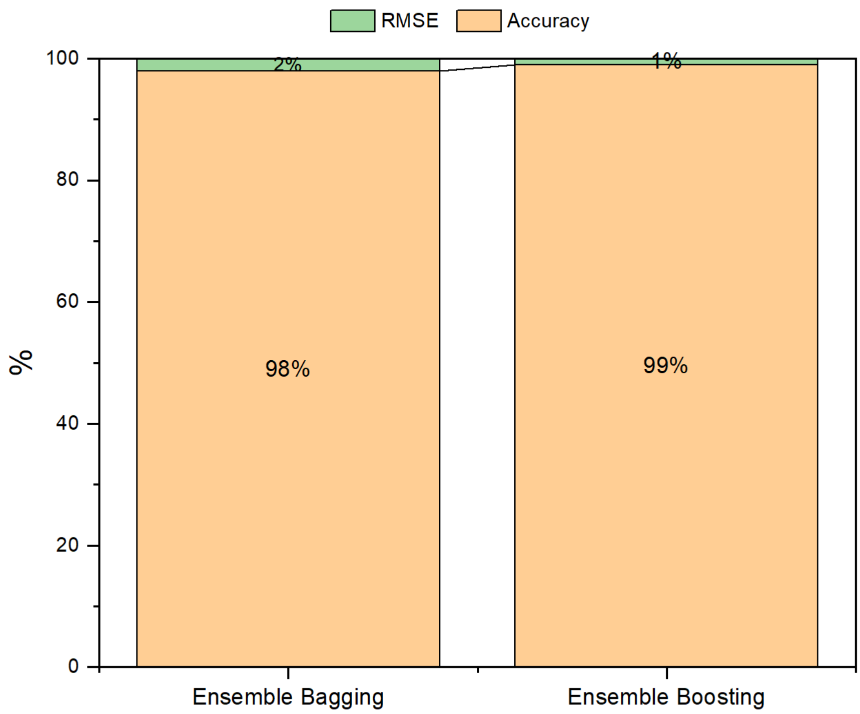


Figure 5.6 Representation of Regressor Algorithm Performance

Upon the successful training, validation, and testing of regression algorithms, a comprehensive analysis was conducted to evaluate the overall performance of the proposed system. In particular, the confusion matrix was utilized as a valuable tool to assess the performance of the classification models, specifically in the domain of medical data analysis. The confusion matrix offers a concise summary of the model's predictions compared to the actual ground truth values, providing insights into the system's effectiveness. The confusion matrix is typically represented as shown in Figure 5.7 to predict whether they have epilepsy based on several features.

Result	Prediction	Actual
True Positive	Epilepsy-YES	Epilepsy-YES
True Negative	Epilepsy-NO	Epilepsy-NO
False Positive	Epilepsy-YES	Epilepsy-NO
False Negative	Epilepsy-NO	Epilepsy-YES

Figure 5.7 General Representation of Confusion Matrix

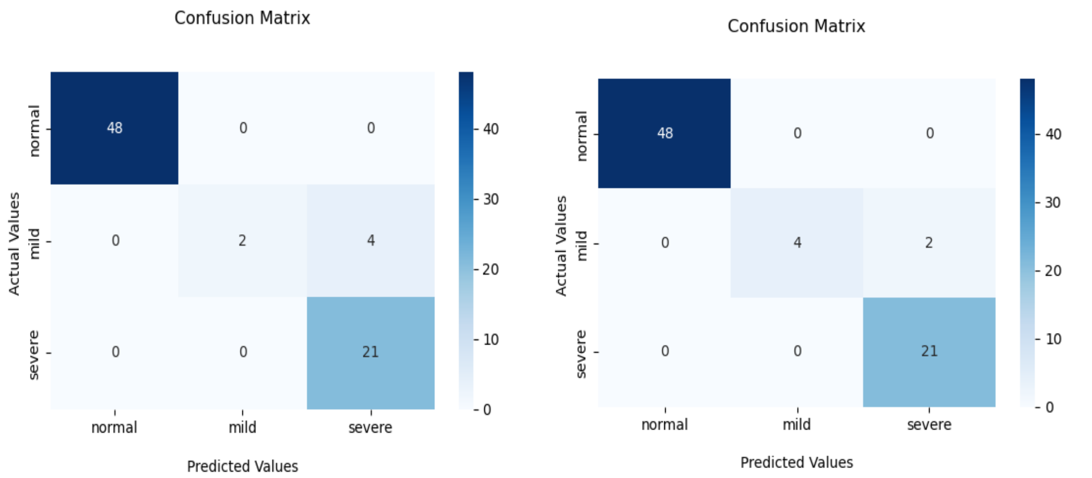
The confusion matrix is a square matrix that consists of four important elements: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Each element represents the count or frequency of predictions falling into these categories. The following table, labelled Table 5.2, presents a comprehensive breakdown of the confusion matrix's four fundamental components.

Table 5.2 Detailed breakdown of key elements in the confusion matrix

Result	Description
True Positive (TP)	The model predicts that the patient has epilepsy (positive) and, indeed, he/she has epilepsy (true prediction).
True Negative (TN)	The model predicts that the patient does not have epilepsy (negative); indeed, he/she does not have epilepsy (true prediction)

False Positive (FP)	The model predicts that the patient has epilepsy (positive), but he/she does not have epilepsy (false prediction)
False Negative (FN)	The model predicts that the patient does not have epilepsy (negative), but he/she has epilepsy (false prediction).

The confusion matrix, depicted in Figure 5.8 (a) for bagging and Figure 5. 8 (b) for boosting, showcases the performance of the proposed test structure for both systems. The diagonal elements, represented in color, indicate the correct categorization of most samples. However, a few samples are misclassified and appear in non-diagonal positions. This observation suggests that the algorithm performs excellently, accurately predicting data during the testing phase.



(**a**) Bagging FLIS (**b**) Boosting FLIS

Figure 5.8 Confusion Matrix for (a) Bagging-FLIS (b) Boosting FLIS

It allows us to assess how well the model performs in identifying patients with the medical condition and those without it. It helps us understand the types of errors the model makes and provides insights into its accuracy and effectiveness.

Latency in machine learning is influenced by both training time and testing time. Training time latency is the duration required to train a machine learning model using a specific dataset. Once the model is trained, it can be applied to predict new, unseen data. On the other hand, testing time latency, also referred to as inference time latency, represents the time the trained model takes to process new data and generate predictions.

To analyze the latency aspects, Table 5.3 provides insights into the bagging and boosting algorithms' training and testing time latency. The findings indicate that the training phase generally takes longer to train the model than the testing phase for both proposed models.

Table 5.3 Latency Time for Bagging and Boosting Algorithm

Parameter	Bagging-FLIS (sec)	Boosting-FLIS (sec)
Training time latency	5.91	3.11
Testing time latency	3.52	2.89

In the case of the boosting-FLIS model, Figure 5.9 demonstrates its overall efficiency in terms of latency, with minimal computation time required for both the training and testing phases. The primary objective in reducing latency in machine learning applications is to achieve faster model training and prediction times, ultimately enhancing real-time performance.

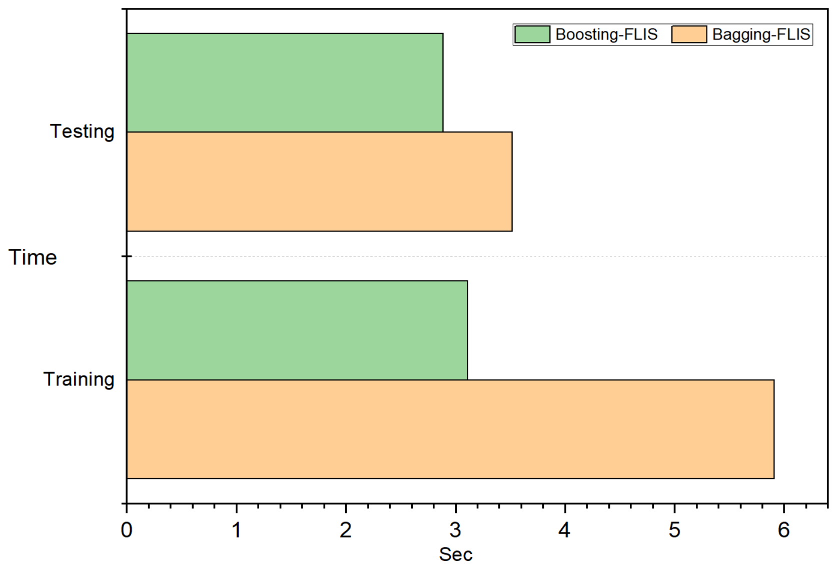


Figure 5.9 Representation of Latency for Bagging and Boosting Model

By analyzing the values in the confusion matrix, several performance metrics such as accuracy, precision, recall (sensitivity), specificity, and F1 score can be derived, which provide a more comprehensive understanding of the model's performance.

Table 5.4 displays the precision, recall, and F-score values for different classes in a classification task. For the "Normal" class, all metrics (precision, recall, and F-score) have a value of 1.00. This indicates that all instances classified as "Normal" are accurate, with no false positives or negatives. In the case of the "Mild" class, the precision is 1.00, meaning that all instances classified as "Mild" are correct. However, the recall is 0.33, implying that only one-third of the actual "Mild" instances were correctly identified. The F-score, which combines precision and recall, is 0.50, indicating a moderate overall performance for this class.

Regarding the "Severe" class, the precision is 0.84, indicating that a substantial portion of the instances classified as "Severe" are correct. The recall is 1.00, suggesting that all actual instances of "Severe" were correctly identified. The F-score is 0.91, signifying a high overall performance for this class.

Table 5.4 Classification Report for Bagging-FLIS

Classes	Precision	Recall	F-Score
Normal	1.00	1.00	1.00
Mild	1.00	0.33	0.50
Severe	0.84	1.00	0.91
macro avg	**0.95**	**0.78**	**0.80**
			Accuracy : 0.95

In conclusion, figure 5.10 demonstrates excellent performance of the classification model for the "Normal" and "Severe" classes, as evidenced by high precision, recall, and F-scores. However, there is room for improvement in accurately identifying instances of the "Mild" class, as indicated by the lower recall and F-score values for this class.

In table 5.4, the macro-averaged (macro avg) provides the average values of precision, recall, and F-Score across all classes for Bagging-FLIS. The macro-averaged precision is 0.95, macro-averaged recall is 0.78, and macro-averaged F-Score is 0.80. These metrics give y an overall sense of how well the model is performing across all classes.

The classification report for ensemble regression-based algorithms with bagging is shown in Annexure III. The accuracy is a measure of how many predictions overall are correct. In Bagging-FLIS, the accuracy is 0.95, indicating that the model's predictions are correct for 95% .

In summary, this table provides a comprehensive overview of your classification model's performance for each class for Bagging FLIS, as well as an overall assessment through macro-averaged metrics and accuracy.

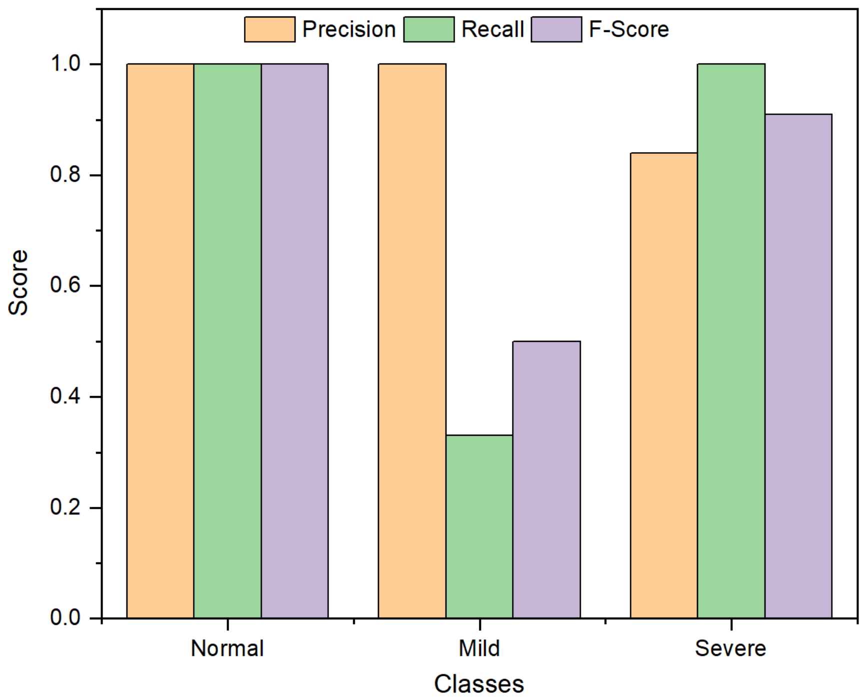


Figure 5.10 Performance of Classification Report for Bagging-FLIS

Table 5.5 contains performance metrics for different classes in a classification problem. These metrics include sensitivity, specificity, negative predictive value (NPV), false positive rate (FPR), and false negative rate (FNR).

Table 5.5 Confusion Matric Parameters for Bagging-FLIS

Class	Sensitivity	Specificity	NPV	FPR	FNR
Normal	1	1	1	0	0
Mild	0.33	1	0.94	0	0.66
Severe	1	0.92	1	0.07	0
macro avg	**0.78**	**0.97**	**0.98**	**0.023**	**0.22**

For the "Normal" class, the sensitivity, specificity, and NPV are all 1.00. This means that the model correctly identifies all instances of the "Normal" class and accurately classifies all non-"Normal" instances without any false positives or false negatives. The FPR and FNR values are 0, indicating no false positive or false negative errors for this class. The sensitivity of the "Mild" class is 0.33, indicating that only 33% of actual instances of the "Mild" class are correctly identified by the model. However, the specificity value is 1.00, meaning that all non-"Mild" instances are correctly classified. The NPV is 0.94, indicating a high probability of correctly identifying instances that do not belong to the "Mild" class. The FPR is 0, indicating no false positive errors, while the FNR is 0.66, indicating that 66% of actual "Mild" instances are incorrectly classified as non-"Mild". The sensitivity of the "Severe" class is 1.00, indicating that the model correctly identifies all instances of the "Severe" class. The specificity value is 0.92, suggesting that 92% of non-"Severe" instances are accurately classified. The NPV is 1.00, signifying a high probability of correctly identifying instances that do not belong to the "Severe" class. The FPR is 0.07, indicating a low rate of false positive errors, while the FNR is 0, meaning there are no false negative errors for this class. Figure 5.11 visualizes the performance of Bagging FLIS, which is very impressive for normal events that occurred during the observation.

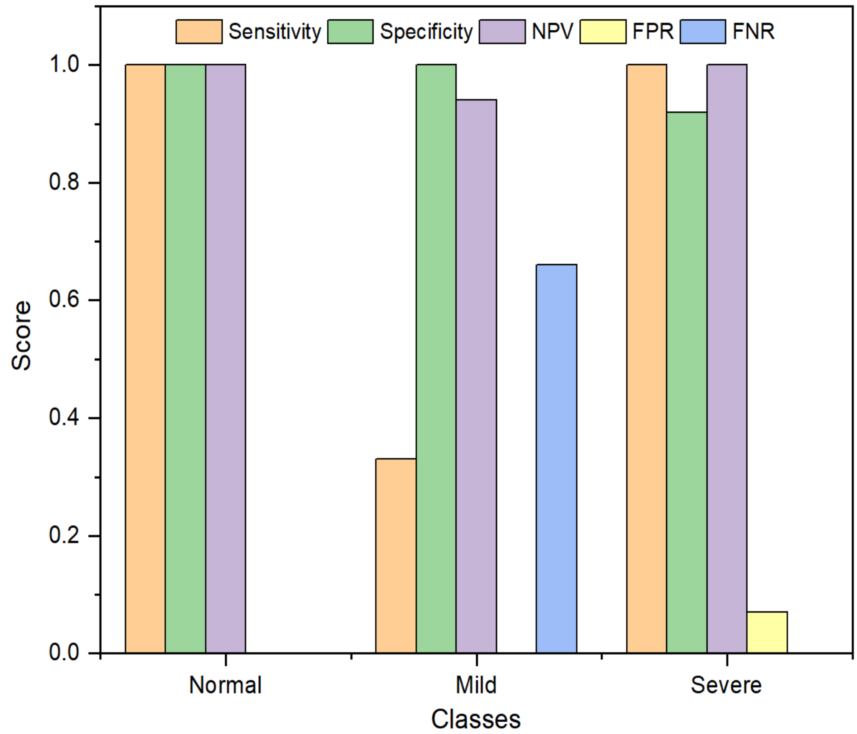


Figure 5.11 Performance parameters for Bagging-FLIS

Table 5.6 presents the classification report for the Boosting-FLIS model. It provides precision, recall, and F-score values for different classes. For the "Normal" class, the precision, recall, and F-score are all 1.00, indicating that all instances classified as "Normal" are correct, with no false positives or false negatives. In the case of the "Mild" class, the precision is 1.00, indicating that all instances classified as "Mild" are correct. The recall is 0.67, suggesting that 67% of the actual "Mild" instances were accurately identified. The F-score is 0.85, reflecting a good overall performance for this class.

Regarding the "Severe" class, the precision is 0.94, indicating that a significant proportion of instances classified as "Severe" are correct. The recall is 1.00, indicating that all actual instances of "Severe" were correctly identified. The F-score is 0.97, demonstrating a high overall performance for this class.

Table 5.6 Classification Report for Boosting-FLIS

Classes	Precision	Recall	F-Score
Normal	1.00	1.00	1.00
Mild	1.00	0.67	0.80
Severe	0.91	1.00	0.95
macro avg	**0.97**	**0.89**	**0.92**
			Accuracy: 0.97

In table 5.6, the macro-averaged (macro avg) provides the average values of precision, recall, and F-Score across all classes for Bagging-FLIS. The macro-averaged precision is 0.97, macro-averaged recall is 0.89, and macro-averaged F-Score is 0.92. These metrics give y an overall sense of how well the model is performing across all classes.

The classification report for ensemble regression-based algorithms with boosting is shown in Annexure IV. The accuracy is a measure of how many predictions overall are correct. In Boosting-FLIS , the accuracy is 0.97, indicating that the model's predictions are correct for 97% .

The boosting-FLIS model in Figure 5.12 exhibits excellent precision, recall, and F-scores for the "Normal" and "Severe" classes. However, there is room for improvement in correctly identifying instances of the "Mild" class, as evident from the lower recall and F-score values for this class.

In summary, this table provides a comprehensive overview of your classification model's performance for each class for Boosting-FLIS, as well as an overall assessment through macro-averaged metrics and accuracy.

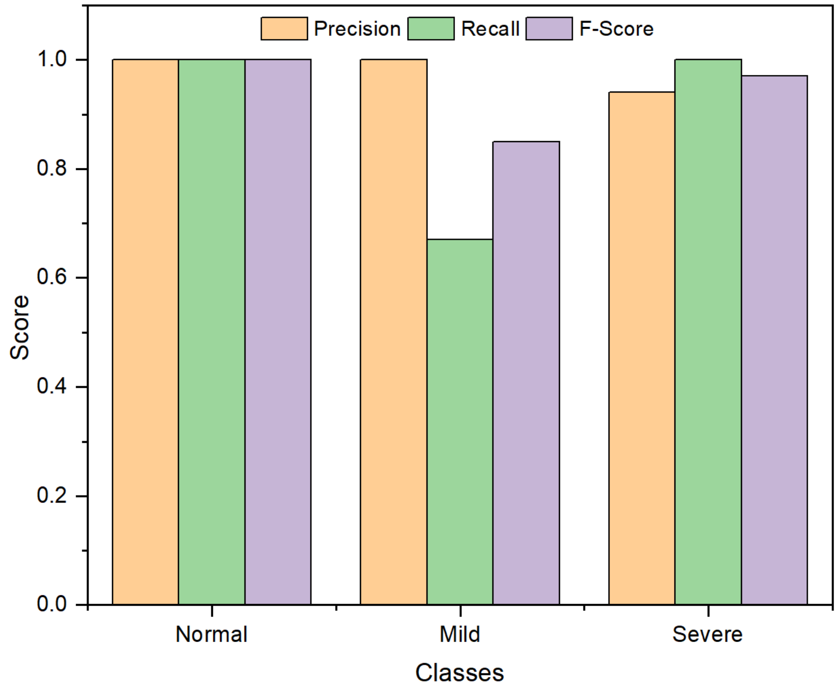


Figure 5.12 Performance of Classification Report for Boosting-FLIS

Table 5.7 displays the sensitivity, specificity, Negative Predictive Value (NPV), False Positive Rate (FPR), and False Negative Rate (FNR) for different classes in the Boosting-FLIS model.

Table 5.7 Confusion Matrix Parameters for Boosting-FLIS

Class	Sensitivity	Specificity	NPV	FPR	FNR
Normal	1	1	1	0	0
Mild	0.66	1	0.97	0	0.33
Severe	1	0.96	1	0.03	0
Macro avg	**0.89**	**0.99**	**0.99**	**0.01**	**0.11**

For the "Normal" class, the sensitivity, specificity, and NPV values are all 1.00, indicating that the model correctly identifies all instances of the "Normal" class without any false negatives, and non-"Normal" instances are accurately classified with no false positives. The FPR and FNR values are 0, indicating this class's absence of false positive and false negative errors. The sensitivity of the "Mild" class is 0.66, indicating that the model correctly identifies 66% of actual "Mild" instances. The specificity value of 1.00 suggests that all non-"Mild" instances are correctly classified. The NPV is 0.97, reflecting a high probability of correctly identifying instances that do not belong to the "Mild" class. The FPR is 0, indicating no false positive errors, while the FNR is 0.33, indicating that 33% of actual "Mild" instances are incorrectly classified as non-"Mild". The sensitivity for the "Severe" class is 1.00, meaning that the model correctly identifies all instances of the "Severe" class. The specificity value of 0.96 suggests that 96% of non-"Severe" instances are accurately classified. The NPV is 1.00, indicating a high probability of correctly identifying instances that do not belong to the "Severe" class. The FPR is 0.03, indicating a low rate of false positive errors, while the FNR is 0, indicating no false negative errors for this class.

Confusion matrix parameters depicted in Figure 5.13 demonstrate each class's sensitivity, specificity, NPV, FPR, and FNR values in the Boosting-FLIS model. These parameters are crucial for evaluating the model's performance and ability to classify instances across different classes correctly.

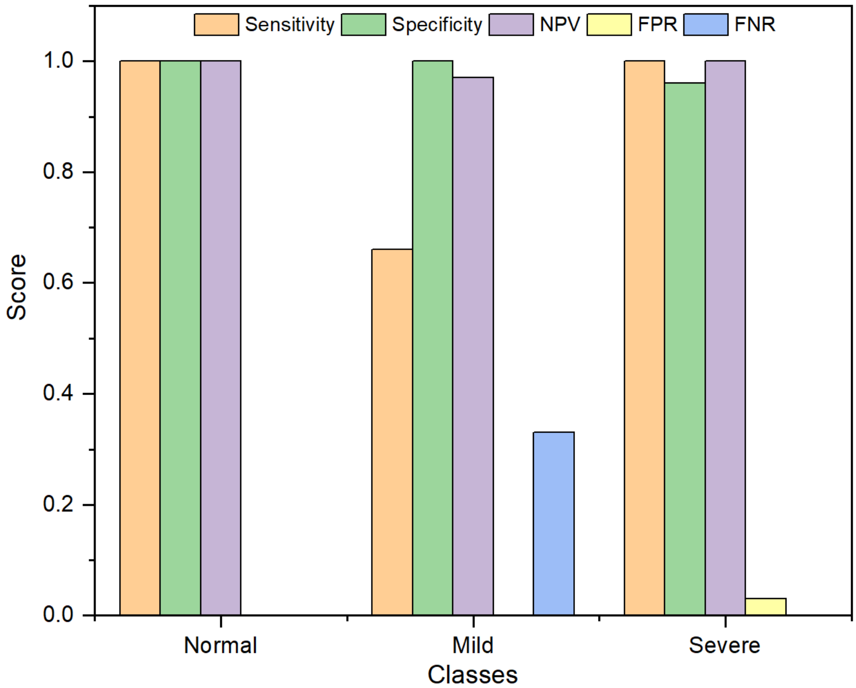


Figure 5.13 Performance parameters for Boosting-FLIS

In conclusion, the Boosting FLIS metrics exhibit slightly superior performance with higher precision, recall, F-Score, and accuracy when compared to Bagging-FLIS. Nonetheless, it's crucial to take into account the particular context and demands of the classification task when analyzing these findings.

The ROC curve is a visual representation used to evaluate the performance of classification models, including bagging and boosting algorithms, as shown in Figures 5.14 and 5.15, respectively. These figures illustrate the assessment of the proposed models by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR= 1 - specificity) at various classification thresholds.

In Figure 5.14, there is a slight change in the shape of the curve at the top right corner, which contributes to a lower area under the curve of 0.99930. This suggests that the model's performance may not be optimal in that region.

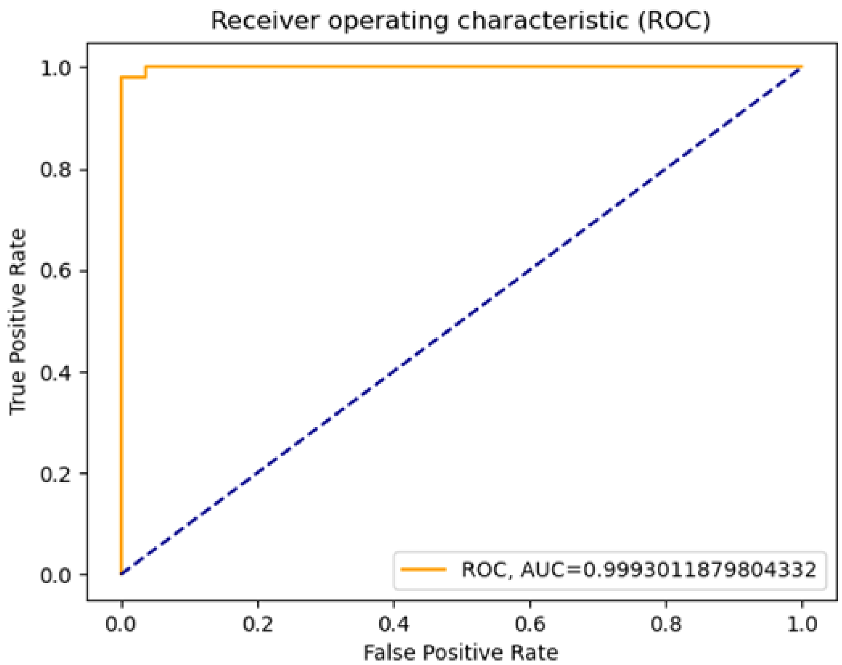


Figure 5.14 ROC for Bagging-FLIS

On the other hand, Figure 5.15 showcases the boosting-FLIS model, which exhibits a significantly high AUC of 1.0. A higher AUC generally indicates superior classification performance, reflecting a higher true positive rate and a lower false positive rate across different threshold values.

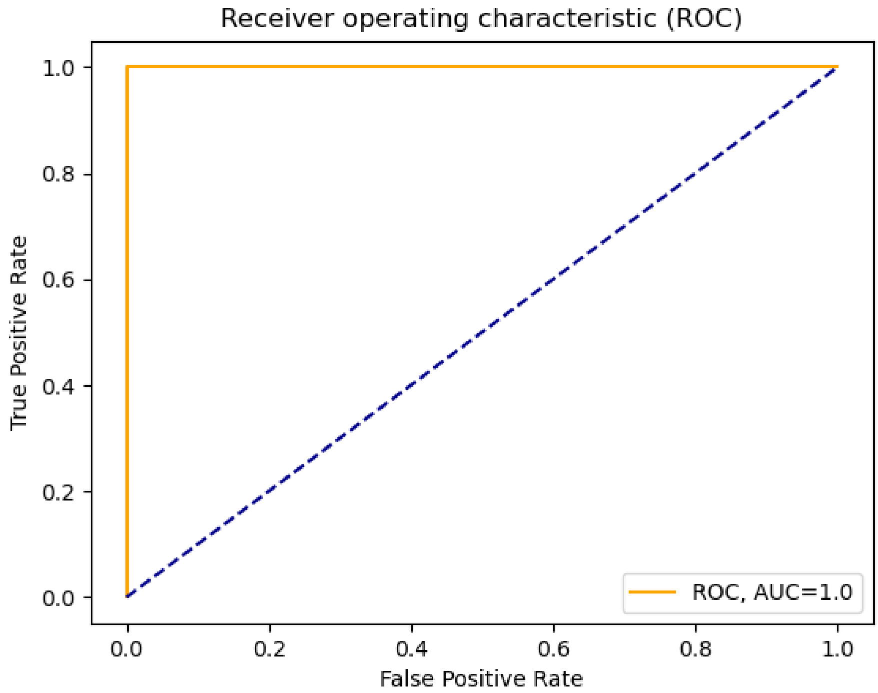


Figure 5.15 ROC for Boosting-FLIS

Overall, by comparing the ROC curves and their corresponding AUC values for bagging and boosting algorithms, the boosting-FLIS model demonstrates a stronger performance in terms of its ability to classify instances accurately and minimize false positives, as evidenced by its notably high AUC in Figure 5.15.

5.4 Comparative Analysis

Table 5.8 compares the proposed system with existing models used by different researchers. The proposed system demonstrates superior performance across several performance measures compared to the existing work. It leverages a fuzzy logic approach combined with ensemble machine learning for better decision-making performance. The proposed method is innovative as it utilizes sensor data and employs effective classification techniques.

Table 5.8 Comparative Performance with Existing Work

Technology/ Methodology [Ref]	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**Error rate**	**F score**
Fuzzy adaptation method [127]	91.8	NI	96.5	NI	NI	NI
Type 2 Fuzzy logic, Inference IoT [126]	95.1	98.1	NI	NI	NI	96.6
Diagnosis of cardiovascular with CNN [110]	NI	NI	NI	NI	20	76
Health monitoring with Fuzzy Logic [112]	92	NI	NI	NI	NI	NI
Classification method [28]	95.5	NI	NI	NI	NI	NI
Telemedicine using ANN and structural equation modelling [138]	96.18	98.36	96.75	96.11	NI	98.16
Audio-based classification, Monitoring [82]	89.35	89.22	NI	NI	NI	NI

Telemedicine platform for disease analysis [117]	80	NI	NI	83	NI	78
Asthama detection, area features[83]	83.89	100	77.8	NI	NI	NI
Diabetic diagnosis, deep learning[86]	86.11	89.3	90.89	NI	NI	NI
Proposed work Bagging (RF)	95	78	97.33	95	2	80.66
Propose work Boosting (Adboost)	97	89	98.66	97	1	92

NI- Not Investigated

Table 5.8 illustrates the proposed system's performance parameters compared to the existing model. It is evident that the accuracy of the proposed model, using the boosting regression approach, specifically AdaBoost, is highly efficient and outperforms existing models, showcasing its superiority in accuracy and various other performance measures.

Figure 5.16 depicts the performance analysis with existing work in terms of accuracy. The average accuracy achieved by the boosting algorithm is 97%. Additionally, the model exhibits a sensitivity of 89%, indicating its ability to identify positive instances correctly.

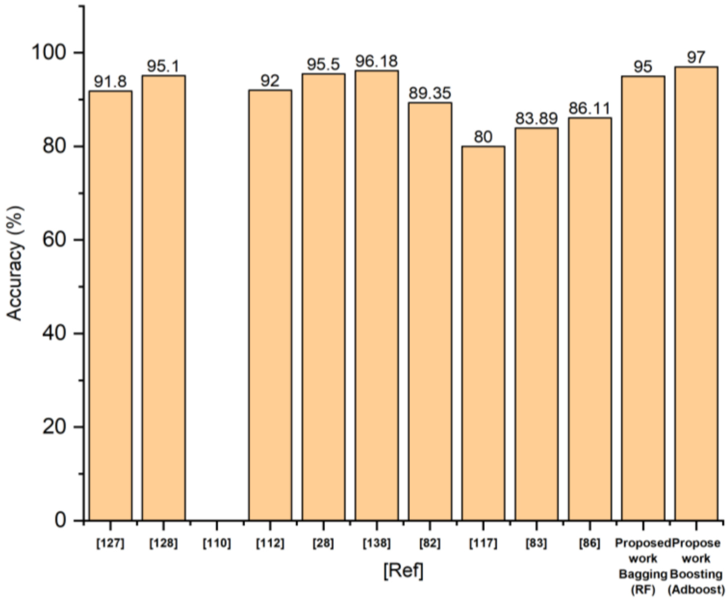


Figure 5.16 Comparative Analysis of Accuracy with the existing method

Figure 5.17 illustrates a comparative Sensitivity Analysis between the existing and proposed methods. However, it is important to note that sensitivity may vary across different research works. Sensitivity measures how well a machine learning model can detect positive instances.

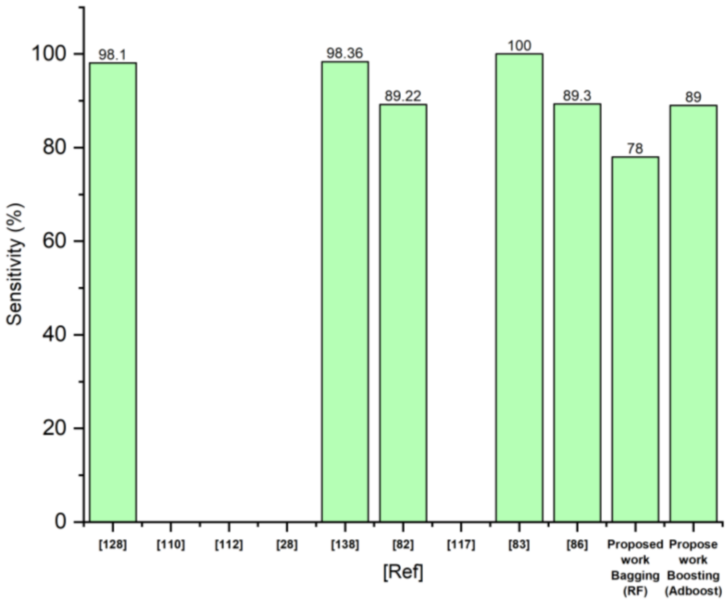


Figure 5.17 Comparative Analysis of Sensitivity with the existing method

Accuracy is the proportion of true results, either true positive or true negative, in an overall sample. For well-proportionate results, true positive and true negative are both important. Hence, accuracy is more important than sensitivity.

We must consider sensitivity and specificity if it is to be considered. The specificity is reported as 98.66%, indicating the model's proficiency in correctly identifying negative instances, as shown in Figure 5.18

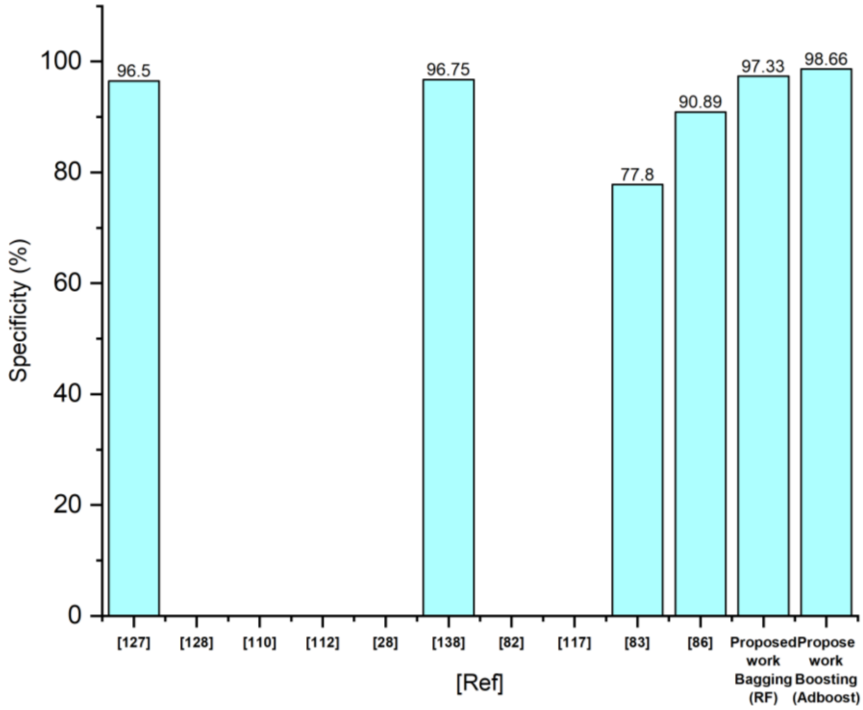


Figure 5.18 Comparative Analysis of Specificity with the existing method

The precision in Figure 5.19 represents the ability of a particular approach to accurately identify positive instances, indicating the proportion of true positive cases among the instances predicted as positive. The precision of the proposed model is 97%, reflecting a low number of false positive predictions. As compared to other existing work.

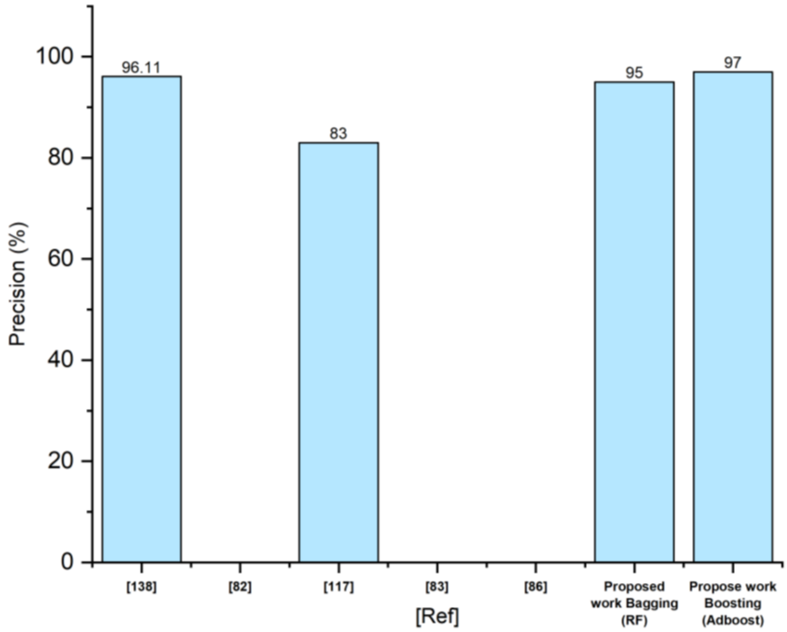


Figure 5.19 Comparative Analysis of Precision with the existing method

Finally, the F-score, which combines precision and sensitivity into a single metric, is reported as 92, indicating a balanced performance in correctly identifying positive instances while maintaining precision, as shown in Figure 5.20.

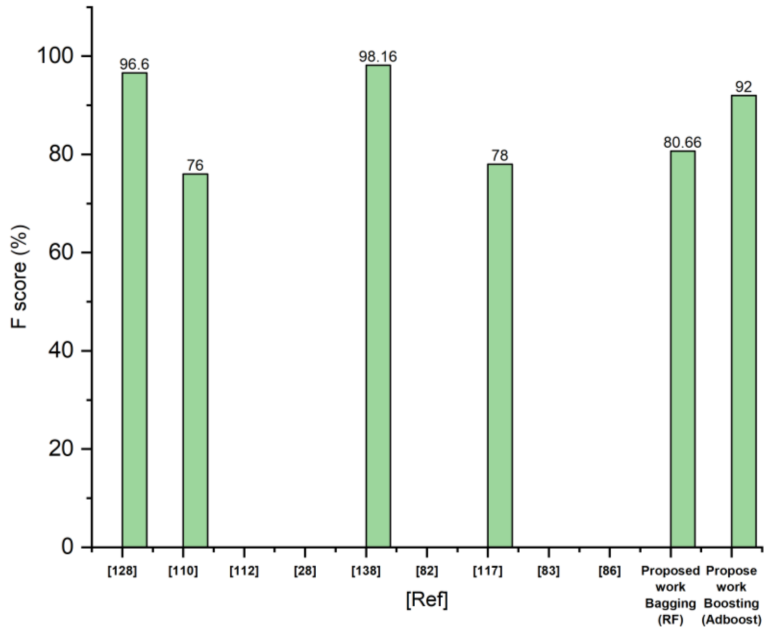


Figure 5.20 Comparative Analysis of F-score with the existing method

Table 5.9 Comparative Analysis of existing epilepsy related work

Parameters	Accuracy (%)	Sensitivity (%)	Specificity (%)	F-score (%)
Ref [43]	NI	92.23	93.38	NI
Ref [88]	90.1	NI	NI	NI
Ref [146]	90.3	86.38	NI	88.56
Ref [148]	92.79	NI	NI	NI
Ref [157]	93.88	NI	NI	91
Proposed Model (AdaBoost-Fuzzy)	97	89	98.66	92

Table 5.9 showcases the performance metrics of various models or methods in a classification scenario, possibly within a research framework. Each model is denoted by reference numbers, with data provided for accuracy, sensitivity, specificity, and the F-score, all presented in percentage form. For instance, Ref [43] demonstrates a sensitivity of 92.23% and a specificity of 93.38%, while Ref [146] has an accuracy of 90.3%, a sensitivity of 86.38%, and an F-score of 88.56%. Conversely, Ref [88] displays an accuracy of 90.1% but lacks sensitivity and specificity data. In contrast, the Proposed Model (AdaBoost-Fuzzy) shows impressive performance with 97% accuracy, 89% sensitivity, 98.66% specificity, and an F-score of 92%. This suggests that the proposed model surpasses the referenced methods in terms of accuracy and maintaining a balanced trade-off between sensitivity and specificity.

Table 5.10 analyses energy requirements for different embedded boards, namely Arduino Uno, Arduino Mega, and the proposed ESP 32 system. It includes voltage levels, current consumption, current consumption during deep sleep, DC current per I/O pin, and DC current for the 3.3V pin.

Table 5.10 Comparative analysis of energy for different board

Embedded Board	Voltage Level	Current Consumption	Current Consumption Deep Sleep	DC Current per I/O pin	DC Current for 3.3V pin
Arduino Uno	5V	45 mA	35 mA	40 mA	150 mA
Arduino Mega	5V	50 mA	500 µA	20 mA	150 mA
ESP 32 (proposed system)	3.3V	15 µA	5 µA	20 mA	40 mA

The proposed ESP 32 system operates at a lower voltage level of 3.3V. It exhibits considerably lower current consumption than the Arduino boards, with 15 µA during normal operation and 5 µA during deep sleep mode. The DC current per I/O pin is 20 mA, and the DC curren for the 3.3V pin is 40 mA. Based on the analysis, it is evident that the proposed ESP 32 system has the lowest energy requirements among the three boards. It consumes significantly less current during both normal operation and deep sleep mode.

Moreover, it requires a lower DC current per I/O pin and for the 3.3V pin compared to Arduino Uno and Arduino Mega. This information is valuable for evaluating and selecting an appropriate embedded board, particularly considering energy efficiency. Lower energy requirements can be advantageous in applications where power consumption is critical, such as battery-powered devices or systems with limited energy resources.

5.5 Summary

In this chapter, considering the prototype model environment, the proposed system is developed, simulated, and analysed based on sensor data collected from the prototype wearable device-based WBAN and IoT for epilepsy classification with intelligent model analytics using a hybrid approach using ensemble machine learning regression and fuzzy logic inference system (EMLR-FLIS). The main predictive model-based regression algorithms with fuzzy logic inference systems are interpreted for the best accuracy with a particular algorithm. Also, the performance of the proposed model is compared with existing work, and it is found that the proposed model is much more capable in every aspect.

CHAPTER 6 CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

New opportunities for healthcare applications like activity identification and patient monitoring are made possible by wireless body area networks. It is important to review and combine their requirements with a feasible computing and communication architecture to get the most out of a network in a distant situation. To bridge the gap between the IoT's network and its perception layer, we have embraced the concept of fog computing. In addition, the Fog server may collect, process, store, and send data elsewhere. The system's design is founded on the Internet of Things; information gathered by WBAN is transmitted to the Fog server, where it is processed before being forwarded to the network layer. The network layer provides reliable routing thanks to an established paradigm. The data is received by the application layer, which then forwards it to the relevant interface. Node MCU, an open-source prototyping platform, is used to create working models of the proposed architecture. The results show that architectural considerations aid in reducing WBAN congestion and ensuring on-time service delivery. Taking into account a wide range of healthcare issues, we want to greatly increase the system's sensor coverage in the near future. Further technology advancements and clinical data collecting are needed to establish whether or not the specified telemedicine system can be deployed in practice.

- The integration of IoT, fog computing, and artificial intelligence in telemedicine offers a promising approach for extending healthcare services to resource-limited rural areas. The proposed IFCATS architecture represents a significant advancement in telemedicine, enabling proactive healthcare and remote disease detection while ensuring robust security measures for sensitive medical data.
- A proposed intelligent hybrid framework, EMLR-FLIS, combines machine learning techniques and fuzzy logic inference to enhance the accuracy of disease prediction. This framework holds great potential for benefiting patients with similar diseases and can improve human health.

- The proposed system's performance has been rigorously evaluated, demonstrating its effectiveness through the comparison of multiple classification methods and performance parameters for machine learning, fuzzy logic, and the fusion of sensor data.
- To differentiate between moderate and severe epilepsy and normal behaviour, the suggested system combined two ensemble machine learning-based classifiers with the fuzzy system, i.e. Bagging -FLISS and Boosting FLIS.
- Compared to state-of-the-art methodologies, the suggested hybrid ensemble boosting machine learning with a fuzzy logic inference system achieves an impressive accuracy of 97%. The model exhibits a sensitivity of 90%, indicating its ability to identify positive instances correctly. In terms of specificity, the model demonstrates a proficiency of 98.66% in correctly identifying negative instances. The precision of the proposed model is 97%, indicating a low number of false positive predictions. The error rate is 1%, highlighting a low overall rate of prediction errors. The F-score, which combines precision and sensitivity, is reported as 92, indicating a balanced performance while maintaining precision.
- The proposed system, utilizing ensemble machine learning and fuzzy logic, proves effective in determining conditions and recommending treatments for epilepsy patients while enabling competent decision-making in treatment, monitoring, and management.
- Furthermore, while the approach has been discussed in a general context, it holds the potential for adaptation in critical settings such as operating rooms, critical care units, infant care, and complex patient scenarios. The results also highlight the advantages of using a machine learning-fuzzy logic system, as it requires a minimal number of devices and software components, making it an optimal choice for intelligent decision-making systems.
- Overall, this research provides significant advancements in epilepsy diagnosis and treatment, showcasing the potential of ensemble machine learning and fuzzy logic in improving healthcare decision-making processes. The findings open doors for further exploration and customization of the proposed system to

cater to specific medical settings and challenging patient cases, ultimately leading to enhanced patient care and improved health outcomes.

- Although the approach has been described generally, it may be modified to be used in more crucial settings such as operating rooms, critical care units, infants, and more difficult patients.
- The results also demonstrate that, due to the small number of devices and pieces of software it requires, a machine learning-fuzzy logic system is an optimal choice for intelligent decision-making systems. The system's implementation aims to enhance efficiency in terms of cost, time, and resource utilization within the existing infrastructure.

6.2 Future Scope

In the future, the increasing availability of health record data presents an opportunity to leverage deep learning algorithms for constructing analytical models that can yield more accurate and effective results. The further system can be enhanced in classification with more health parameters and precise acquisition of parameters reading. Also, low-cost, reliable, and precise measurement wearable device development is challenging for any disease diagnosis. The main concern is the security of health records, so concern-secured protocols must be used to preserve patients' privacy.

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List of Conferences and Publications

- "Comparative Analysis of e-Health Care Telemedicine System Based on Internet of Medical Things and Artificial Intelligence," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2021, pp. 1768-1775, doi: 10.1109/ICOSEC51865.2021.9591941.

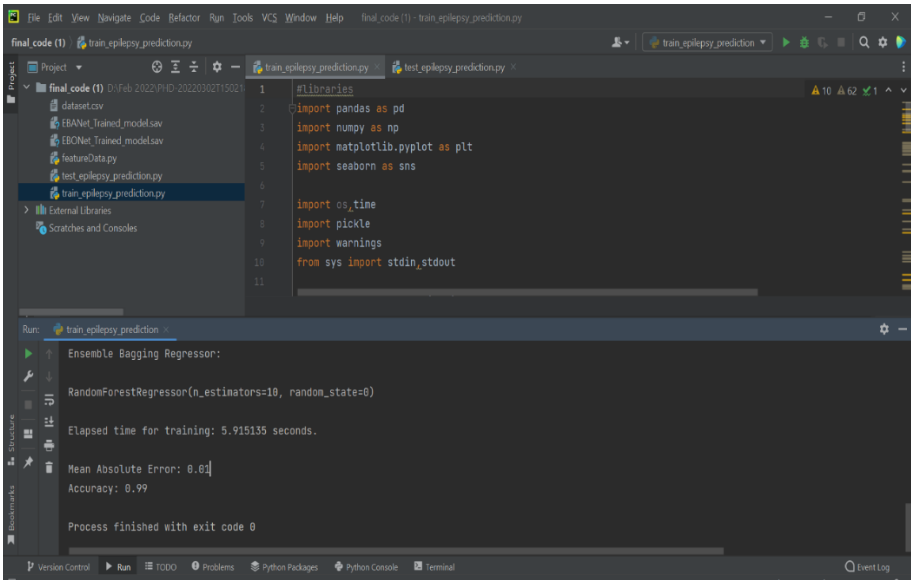
- "A novel scheme for classification of epilepsy using machine learning and a fuzzy inference system based on wearable-sensor health parameters," *Sustainability*, 14(22), sp. 15079. Available at: https://doi.org/10.3390/su142215079.

- "Fog-enabled framework for patient health-monitoring systems using internet of things and Wireless Body Area Networks," *Lecture Notes in Electrical Engineering*, pp. 607–616, 2023.

Annexure

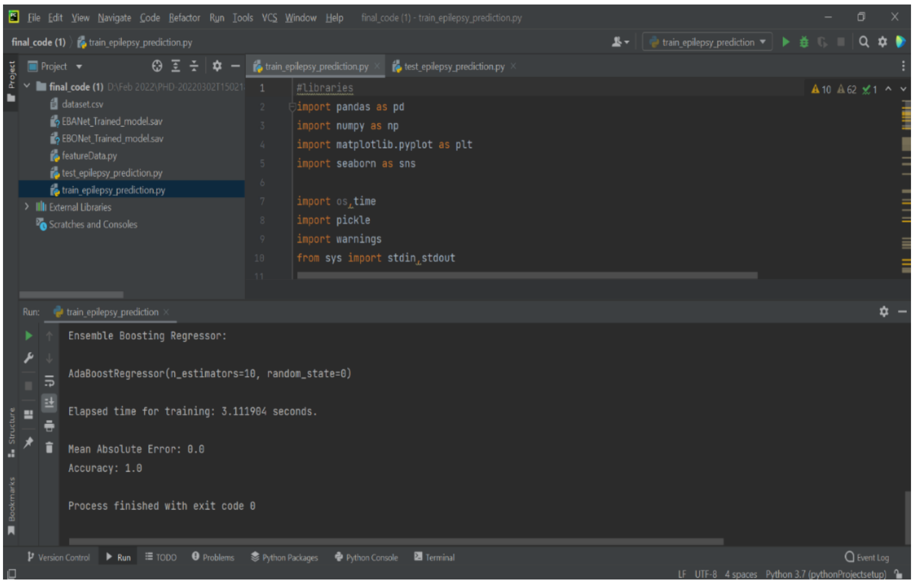
Annexure-I

Snapshot of simulate result for Ensemble Bagging for trainig dataset



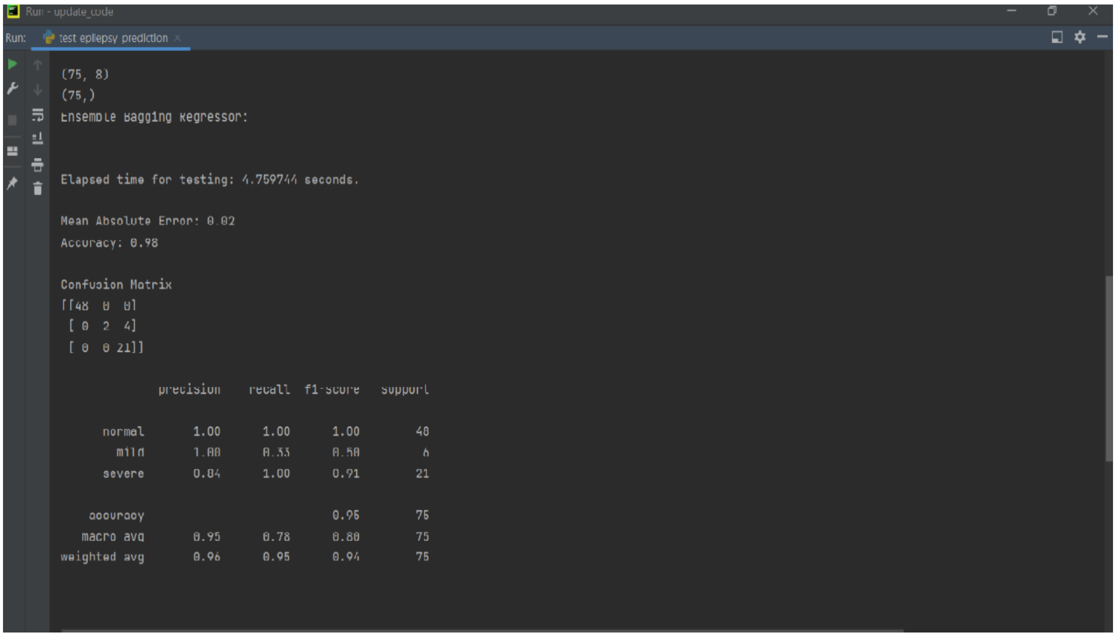
Annexure-II

Snapshot of simulate result for Ensemble Boosting for trainig dataset



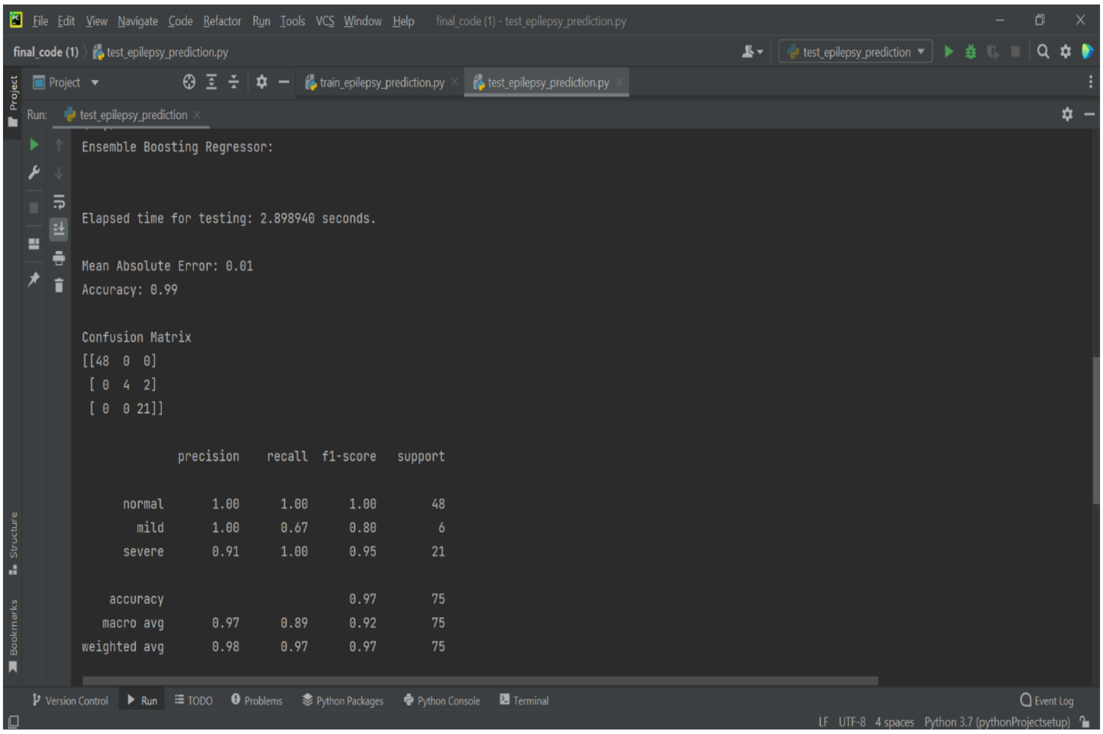
Annexure-III

Snapshot of classification report of Bagging regressor model



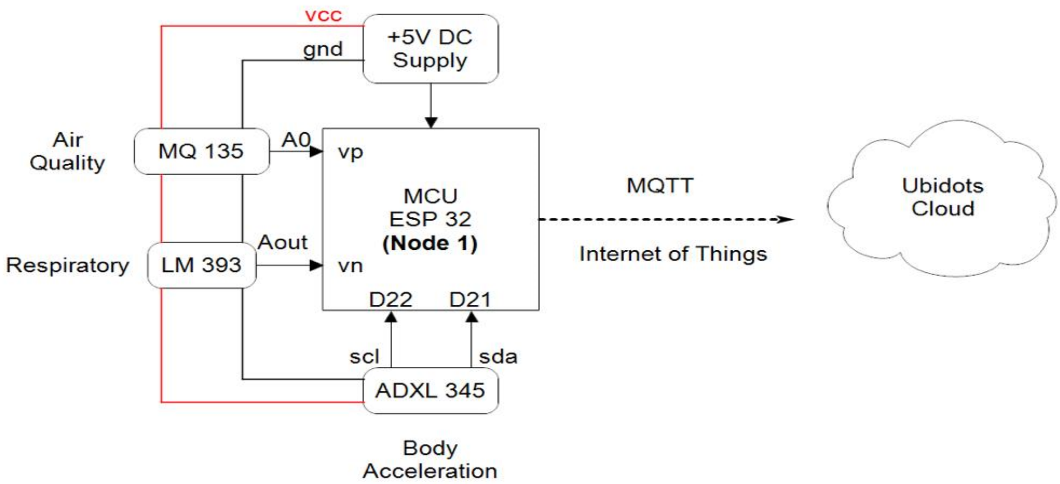
Annexure-IV

Snapshot of classification report of Boosting regressor model



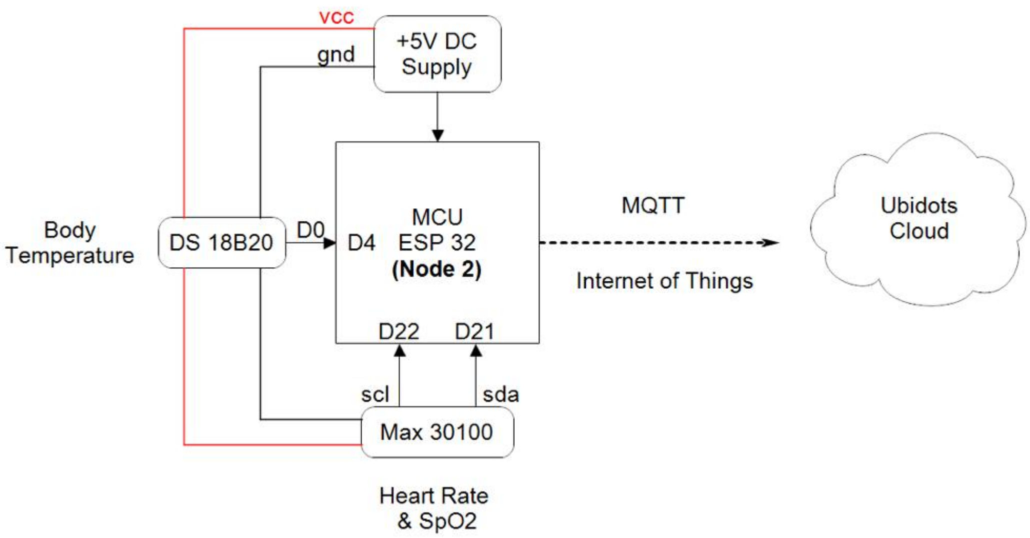
Annexure-V

Circuit Block Diagram for node 1



Annexure-VI

Circuit Block Diagram for Node 2



Annexure-VII

Request letter for dat acollection

To,
Dr. Somesh Chaudahry
MBBS, TDD
(Ch.Medicine)

Through: Dr. Manwinder Singh, Associate Professor, Lovely Professional University,

Punjab**Applicant:**AnkushKadu.ResearchScholar,LovelyProfessionalUniversity,Punjab**Subjec**

t: Regarding some questionnaires and data collection related to epilepsy

diseaseRespectedSir/madam,
Wearewritingthisletterinregardtotherequestforsomequestionnairesanddatacollectionrelatedtoepilepsy diseaseunderyour expertguidanceandsupervision.

Weareconductingresearchonentitled"ANALYSISOFMACHINELEARNINGBASEDTELEMEDICINESYSTEMFORREMOTEDISEASEDIAGNOSISUSINGFOGCOMPUTINGANDINTERNETOFMEDICALTHINGS (IoMT)".

Forthisreason,Iamrequestingyoupermitmetoaccesstheinformationfortheearlydetectionofepilepsydiseasesat apreliminarystage.

In this regard, it is requested to answer the attached questionnaireThe questionnaire is designed to findout which parameters are important for the early detection of epilepsy disease and what would be thenormalrangevalue for theparameters.

The intention of our work is to use that information and data in order to help in the early detection ofepilepsydiseasesatthepreliminarystage.Therefore,informationwillbeveryhelpfulforusregardingthismatter.

For the data collection purpose, we will provide you developed wireless body area network model whichwecan beeasily fixed onthe patient'sbody.

All the information provided herein will be used for research purposes only and won't, in any manner.Weheartilyexpressourgratitudeforyourexpertguidanceregardingthis.Weassureyouthatallprotocols andrules, andregulationswillbefollowed, and privacyregulations adhered to.

Your corporation is highly appreciated. Hope you will consider our request and oblige us.Thankingyou,
Withregards,

Dr.ManwinderSingh
AssociateProfessor
LovelyProfessionalUniversity,Punjab

AnkushKadu
Ph.DScholar
LovelyProfessionalUniversity,Punjab

Questinaaire and discussion with Doctore for Epilesy

Questionnaire for Epilepsy

By:
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As per the WHO Prevention of Epilepsy Disease

An estimated 25% of epilepsy cases are potentially preventable.

- Preventing head injury, for example by reducing falls, traffic accidents and sports injuries, is the most effective way to prevent post-traumatic epilepsy.
- Adequate perinatal care can reduce new cases of epilepsy caused by birth injury.
- The use of drugs and other methods to lower the body temperature of a feverish child can reduce the chance of febrile seizures.
- The prevention of epilepsy associated with stroke is focused on cardiovascular risk factor reduction, e.g. measures to prevent or control high blood pressure, diabetes and obesity, and the avoidance of tobacco and excessive alcohol use.
- Central nervous system infections are common causes of epilepsy in tropical areas, where many low- and middle-income countries are concentrated. Elimination of parasites in these environments and education on how to avoid infections can be effective ways to reduce epilepsy worldwide, for example those cases due to neurocysticercosis.

Details Available at: https://www.who.int/news-room/fact-sheets/detail/epilepsy

To detect and prevent epilepsy at a preliminary stage, we have some questionnaires which would be very helpful for conducting research. Also to make a decision that which parameters are important early detection of diseases.

Observations:

- Stress Fact/ Migraine
- Pressure Complaints & Idiopathic / Alcoholic addiction
  Pregnensi Complication

Sr. no.	Health Parameters	Remark	Symptoms	Normal Ranges
1	EEG	YES	Abnormal	Graph base
2	Body Temperature	YES	High	< 36.5 °c
3	Oxygen level	Rare Case	Low	above 95 %.
4	Heart Rate	YES	High	60 - 90 ppm
5	Respiratory Rate	YES	Low	12 - 16 bpm
6	Pulse	YES	High	60 - 90 ppm
7	Mental Stress	yes	High	observation
8	CT/MRI	yes	Abnormal	Report base
9	Air Quality	May be	----------	< 100 ppm

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Annexure-IX

Certificate of Reference data

CERTIFICATE

It is to certify that Ankush Kadu, PhD Scholar from School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab bearing Reg. No. 41900774 has interacted with the professionals on his PhD Topic "ANALYSIS OF MACHINE LEARNING BASED TELEMEDICINE SYSTEM FOR REMOTE DISEASE DIAGNOSIS USING FOG COMPUTING AND INTERNET OF MEDICAL THINGS (IoMT) " under the guidance of Dr. Manwinder Singh, Associate Professor, School of Electrical and Electronics Engineering of Lovely Professional University, Phagwara, Punjab.

Detection and prevention epilepsy at a preliminary stage for conducting research were discussed and Primary Data for the same has been generated through WBAN moduleis provided to the PhD Scholar.

Name & Signature

Dr. Somesh Chaudhary

MBBS,TDD

(Ch. Medicine)

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