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Intelligence Furnished by Fog Intelligent Clinical Decision Support System for Healthcare Applications (FICDSS)

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Abstract: Wearable devices are widely utilised in intelligent healthcare systems. Recognising and understanding physiological data from medical sensor equipment is crucial for smart healthcare. Fog computing analyses physiological data to reduce cloud computing's latency. Smart healthcare, however, has substantial hurdles in a fog environment because to delay for emergency health status and overloading. Here, we offer the first ever Fog-enabled Intelligence Clinical Decision Support System (FICDSS) for detecting physiological parameters. The goal of this system is to increase the efficiency of medical treatment and diagnosis by employing intelligent systems. The suggested system is composed of four distinct layers: the sensor layer, the edge layer, the fog layer, and the cloud layer. At the edge layer, a microcontroller unit receives data from wearable health sensors. At the fog layer, an intelligence system is deployed with fuzzy logic and machine learning systems based on the context and type of data that predicts the health diagnosis. At the cloud level, the results of the sensors and the most up-to-date information are shown. Both the cloud and fog layers adjust rapidly to the user's vitals. The proposed experimental simulation is built and analysed based on several analytical parameters, detection accuracy, and latency.

Keywords: *Clinical Decision Support System, Fog Computing,Healthcare,Internet of Things,Fuzzy Logic System, Machine Learning System*

I. Introduction

Accurate and prompt decision making is crucial to providing excellent patient care. Clinical decision support systems (CDSS) have emerged as useful tools for assisting healthcare professionals in making informed decisions by integrating patient data, medical experience, and cutting-edge technologies. The advancement of intelligent CDSS in healthcare has been greatly influenced by fog computing, which moves intelligence and processing power closer to the data source. Using the strengths of intelligent systems and fog computing, the FICDSS is a game-changing approach to enhancing clinical decision-making in healthcare applications [1]. FICDSS integrates intelligent systems like machine learning, fuzzy logic, and expert systems with the benefits of Fog Computing including low latency, real-time data processing, and edge intelligence to deliver effective and context-aware decision support. The primary objective of FICDSS is to improve the accuracy, speed, and efficiency of clinical decision-making by facilitating intelligent analysis of patient data at the network's edge. The FICDSS can organise and analyse large amounts of healthcare data to draw conclusions and make suggestions for practitioners to follow [2]. The Edge layer consists of edge devices and gateways that perform preliminary data processing and filtering [3] to enable real-time analysis and reduce data transmission to the Fog and Cloud layers. The fog layer employs smart systems to do advanced analytics. These analytics include context-aware reasoning, predictive modelling, and the merging of disparate data sets. The data is analysed using expert systems, machine learning algorithms, and fuzzy logic to provide useful insights. The patient's unique characteristics, medical advice, and domain knowledge are all taken into consideration by the context-aware reasoning to provide tailored decision support [4]. The Cloud layer consolidates patient information, medical knowledge databases, and teamwork tools for healthcare providers. It enables long-term data storage and the analysis of large datasets for the sake of discovery and enhancement. Overall, FICDSS offers a variety of benefits in the medical field. Improvements in clinical decision-making are achieved by the provision of individualised, real-time, context-aware decision support. Improved patient outcomes, reduced medical errors, and maximised use of available resources are all feasible thanks to early detection and intervention [5]. In addition, FICDSS allows for telemedicine, remote monitoring, and easy integration with preexisting healthcare infrastructure. When fog computing is combined with intelligent systems, as in the

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Fog Enabled Intelligence Clinical Decision Support System (FICDSS), revolutionary changes can be made in healthcare applications [6]. In the age of intelligent healthcare systems, it equips medical professionals with cutting-edge decision-making tools, promotes pro-active care for patients, and paves the way for improved health outcomes.

II. Literature Review

In recent years, a rising corpus of research that studies the uses of artificial intelligence (AI) in the medical area as well as its implications has been published. This study has been published in increasing numbers [7-10]. This encompasses both advantageous and disadvantageous results. A plethora of studies have shown that artificial intelligence had the potential to change a multitude of processes within the healthcare business. One of these processes is patient care. These operations include of performing a diagnostic, formulating a treatment plan, monitoring a patient's condition, and providing medical care [11-15]. For instance, research has demonstrated that AI systems are capable of successfully evaluating medical pictures, which can aid radiologists in finding anomalies and boost the diagnostic accuracy of their job. AI systems also have the potential to assist in the development of new medical treatments. In addition, it has been proved that prediction models based on AI have the capacity to effectively anticipate patient outcomes and identify individuals who are at an elevated risk of having particular diseases [16-19]. In addition, artificial intelligence-powered virtual assistants and chatbots have been created in order to ease remote patient monitoring, facilitate patient involvement, and deliver individualised healthcare information. In the realm of medicine, there have been a variety of difficulties and ethical issues that have been brought up in connection to artificial intelligence [20]. These concerns include the necessity for solid regulatory frameworks, as well as problems with the privacy of patient data and algorithmic prejudice. Additionally, there are worries regarding the impact of algorithmic bias. It is necessary to do further research in order to solve these challenges and reach the full potential of AI in terms of improving patient outcomes and creating best practises in the delivery of healthcare [21-25].

Intelligent systems are being integrated into an expanding number of disease-related operations. Therefore, computational intelligences are significantly contributing to the present age by creating cutting-edge methods for treating and diagnosing severe illnesses. A large variety of truth values are acceptable to fuzzy logic. These standards are typically unspecific and open to several interpretations [26-29]. Fuzzy-based intelligent systems may easily accommodate model changes without necessitating equivalent adjustments to the underlying detection logic. The knowledge base has loosened the system's coupling and provided fuzzy logic with more leeway. Predictive analytics are driven by predictive modelling, which may be taught over time to react to new data or values and provide insights into patients' health.[30-38

III. Methods

A. Proposed Intelligent Model

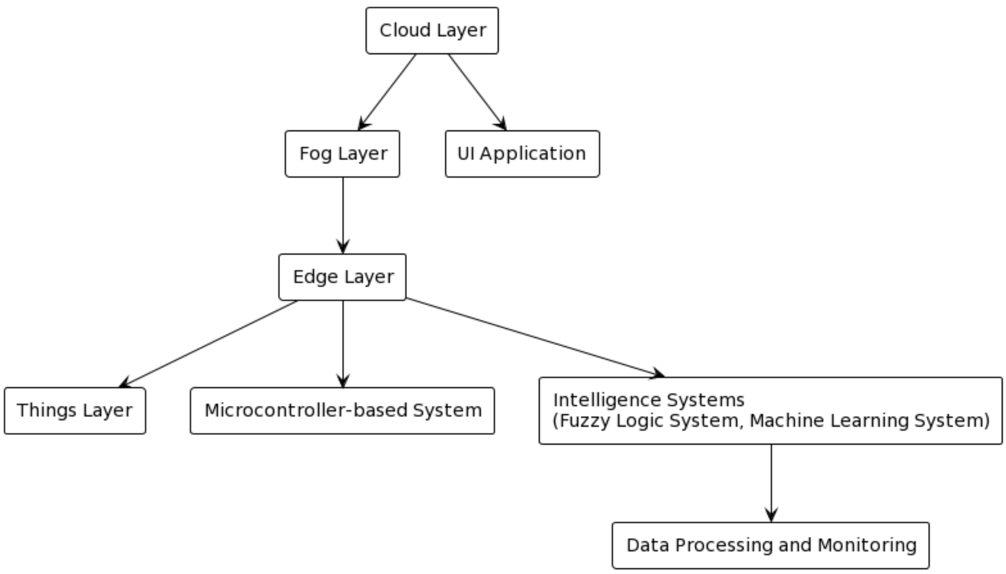

Figure 1: Proposed FCDS System

a. Things Layer: The sensors used in healthcare applications are represented by this layer. These sensors include body temperature, blood pressure, heart rate, blood oxygen saturation, breathing rate, blood sugar level, body position accelerometer, ECG, and EEG.
b. In order to diagnose diseases, these sensors are connected to wearable body sensors.
c. The edge layer is made up of a microcontroller-based system that is in charge of gathering information from sensors that are attached to patients or persons.
d. For data processing and monitoring, the gathered data is handled at the fog/cloud layer.
e. The fog layer is made up of intelligence systems that are based on several context situations, including fever, hypertension, heart disease, diabetes, geriatric patients, and COVID-19-affected individuals.
f. For rule-based and predictive health diagnosis at the fog layer, an intelligent system made up of a fuzzy logic system and a machine learning system is used.
g. The cloud layer receives the processed data and uses it to monitor patient health information in real time.
h. The data and context information are all stored in the cloud layer.
i. A UI application is included for monitoring by doctors, carers, personal use, or any other authorised users.
j. The suggested framework depicts the FCDSS architecture's layers, starting with the Things Layer with a variety of health sensors, moving through the Edge Layer for data collection, moving on to the Fog Layer for intelligent health diagnosis, and finally arriving at the Cloud Layer for storage and monitoring with the UI application**.**

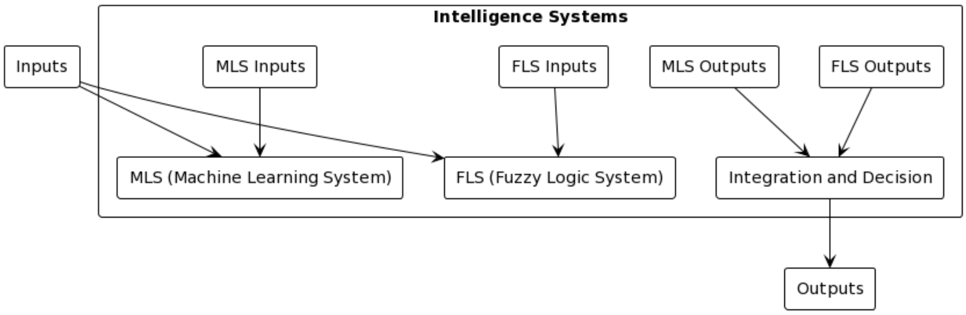

Fig 2: Intelligent system workflow of FCDSS

IV. Implementation of Fuzzy Logic System (FLS)

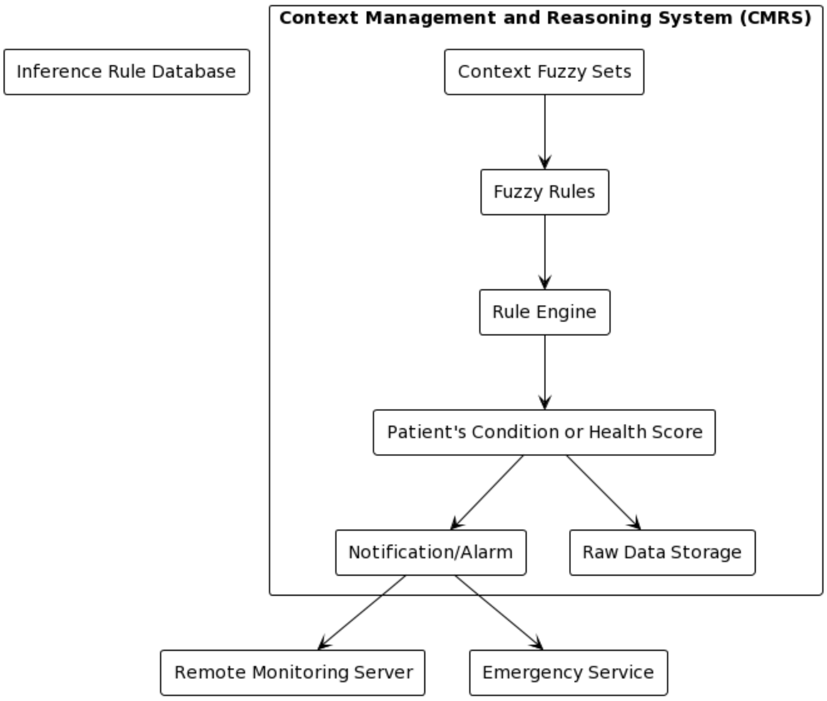

Fig 3: CMRS-FCDSS System Design

a. Context Fuzzy Sets: Represents the fuzzy sets produced by fusing analysis of the raw sensor data with context knowledge.
b. Describes the collection of fuzzy rules that were imported from the inference rule database.
c. Rule Engine: Uses fuzzy rules to infer the patient's present state of health or to produce higher-level context.
d. Patient's Condition or Health Score: Displays the results based on the fuzzy inference that show the patient's current condition or health score.
e. If the output is urgent or abnormal, this is the notification or alert that is delivered to the remote monitoring server.
f. Raw Data Storage: Indicates the keeping of raw data for upcoming analysis and decision-making.
g. The collection of fuzzy rules that the CMRS uses for inference and reasoning are included in the inference rule database.
h. Remote Monitoring Server: This is a representation of the server in charge of obtaining and handling alerts or notifications.

Represents the emergency service that may be contacted in the event of an emergency

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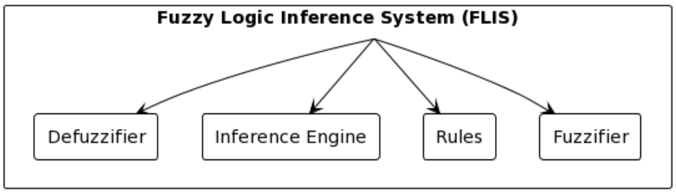

Fig 4: Block diagram of FLIS

a. Fuzzifier: Creates fuzzy numbers from exact input numbers, which are required for fuzzy logic processing.
b. Describes the collection of fuzzily defined rules that make up the rule base.
c. Fuzzy outputs are produced by the inference engine, which applies the fuzzy rules to the fuzzy input.
d. Defuzzifier: Uses a defuzzification technique to transform the hazy output into a clear or quantifiable conclusion.

The Figure 4. show the workflow and key elements of the proposed system's Context Management and Reasoning System (CMRS) and Fuzzy Logic Inference System (FLIS), which are both utilised for context reasoning and health diagnostics.

Algorithms used for implementation is summarized below.

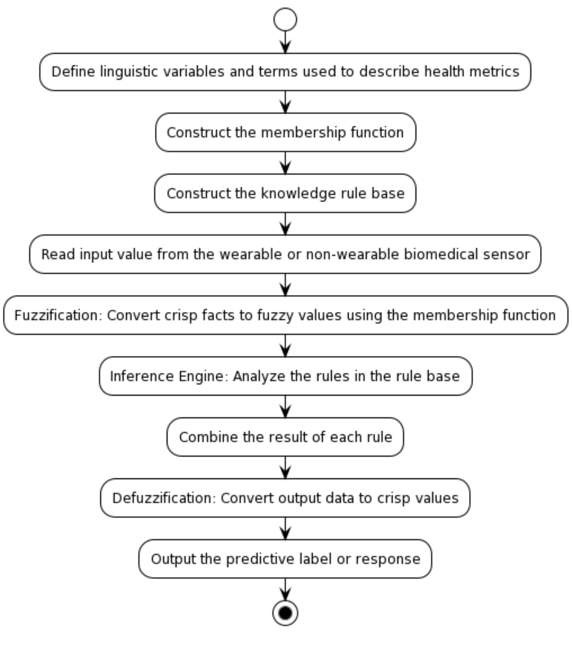

Fig 5. Context Management and Reasoning System (CMRS)

The contexts created and outlined by the WHO and utilised to understand various health indicators are summarised in Table 1. In order to help portray the patient's severity, the thresholds of several health measurements are transformed into the corresponding linguistic values of Safe and Unsafe. The FLIS assigns a label (Good, Fair, Serious, or Critical) based on a set of health criteria, reflecting the patient's state of health.

Table 1: Expertise Knowledge used for FLIS

Health Parameters	Facts (Safe)	Facts (Unsafe)
Body Temperature	36.1-37.2 degcel	Greater than 38 deg cel = Fever
Blood Pressure	Less than 120 mmHg (sys bp), less than 80 mmHg (dysbp)	Greater 120-80 mmHg
Heart Rate	60-100 beats per minute	Below 60, greater 100
Oxygen Level in Blood	95% higher	Less than 95%
Breathing Rate	12-20 breaths per min	Under 12 or over 25
Sugar Level	100-200 mg/dL	More than 200 mg/dL

V. Implementation of Machine Learning System (MLS)

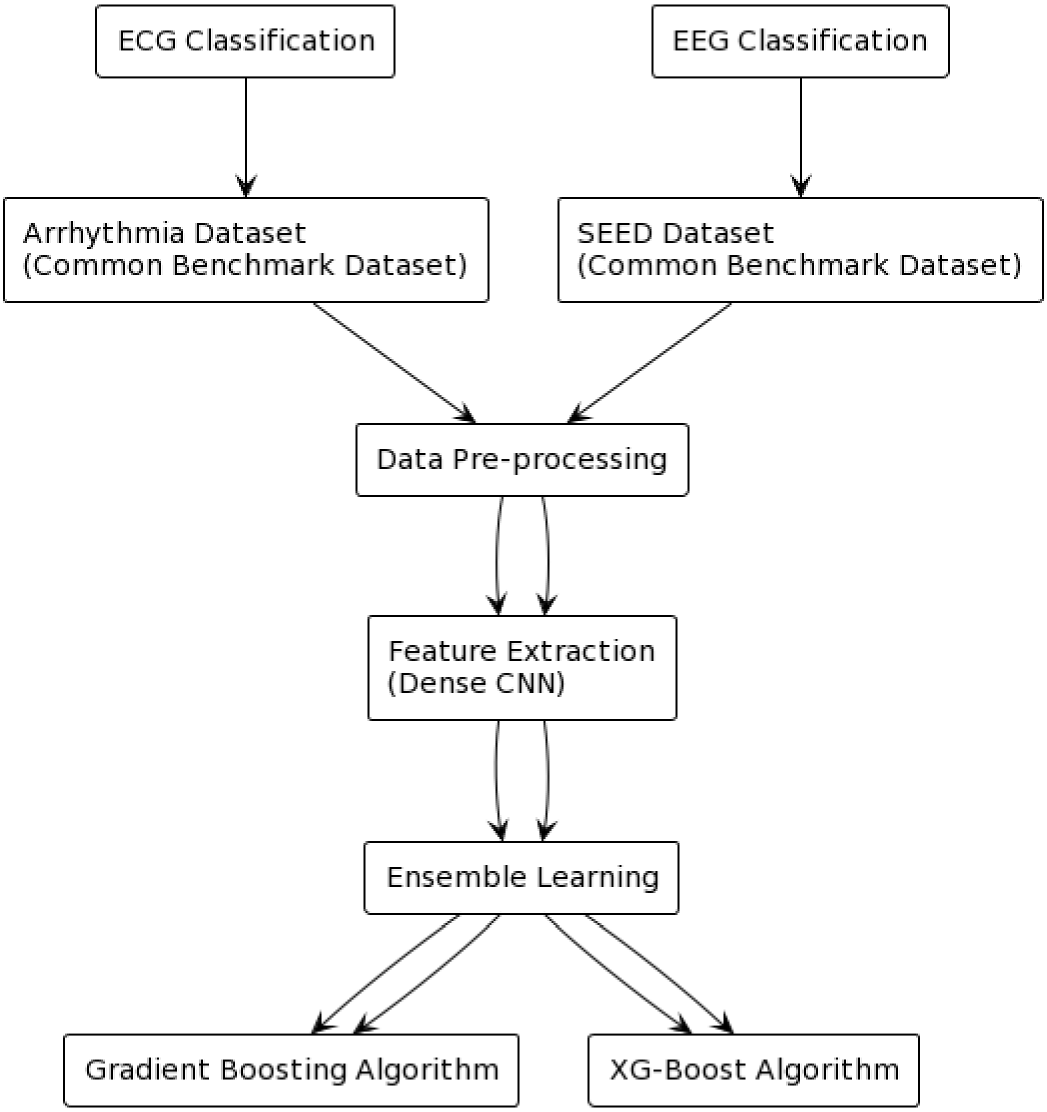

Fig 6. Machine Learning System (MLS)

a. Data pre-processing: In this stage, features are transformed by being scaled to a particular range during data pre-processing.
b. To make sure they lie inside the desired range on the dataset samples, each feature is scaled and translated independently.
c. The dataset should be standardised for machine learning estimators to perform at their best.
d. Feature Extraction (Dense CNN): In this stage, low to high-level semantic characteristics from ECG and EEG recordings are extracted using a Dense CNN (Convolutional Neural Network).
e. To produce meaningful representations, the pre-processed data is applied to the Dense CNN.
f. When using numerous learning algorithms to attain a greater expected performance than any single method, ensemble learning is favoured for data categorization.
g. To provide the final predictions, the algorithm aggregates the outcomes from several decision trees.

A. Algorithm for MLS for ECG

h. Gradient Boosting Algorithm: The ensemble learning stage uses the gradient boosting algorithm.
i. It makes predictions by combining the output from many decision trees.
j. Both categorical and continuous target variables can be utilised with the model.
k. Another method utilised in the ensemble learning stage is the XG-Boost method.
l. In comparison to the Gradient Boosting Algorithm (GBM), it is quicker since it supports parallel preprocessing.
m. Missing values can be handled by the XG-Boost model on its own.

The graphic gives a visual depiction of the MLS technique's implementation method for categorising ECG and EEG data. It shows how to use the Gradient Boosting Algorithm and XG-Boost Algorithm for ensemble learning after feature extraction from the pre-processed data.

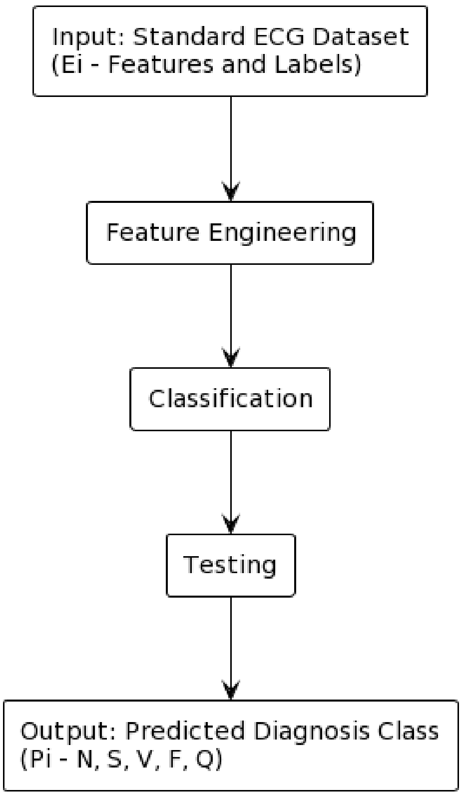

Fig 7. *MLS for ECG*

a. The standard ECG dataset (Ei), which contains both features (information about the ECG signals) and labels (the appropriate diagnostic classes), serves as the algorithm's input.
b. Feature engineering is the stage when the input data is cleaned up and prepared for categorization.
c. The feature data and target data sizes are determined by the algorithm.
d. The approach performs scaling transformation to each sample in the feature data to normalise the data and guarantee equal distribution across various diagnostic groups.

e. The subsequent phase of categorization receives the processed data.
f. The method learns models to categorise the ECG data into several diagnostic classifications during this phase of classification.
g. Initialization is done on the parameters for ensemble model training.
h. To discover the ideal hyperparameters for the models, the technique use grid search optimisation.
i. The chosen hyperparameters are used to train the models.
j. By minimising the training loss, the method verifies the learned models.
k. Finally, a knowledge repository stores the learned models for further use.
l. Testing: The algorithm enters the testing phase, when it diagnoses new, unseen ECG data using the taught models.
m. The algorithm is fed user test data.
n. The test data are subjected to feature engineering procedures comparable to those carried out in the preceding phase.
o. The loaded trained models from the knowledge repository.
p. Using the supplied models, the computer guesses the EEG signals' emotions and categorises them as positive, negative, or neutral.
q. Output: The method generates the anticipated diagnostic class (Pi), which is equivalent to each of the classes.

The method examines the incoming data, applies feature engineering, trains classification models, evaluates the models using fresh data, and then outputs the projected diagnostic class.

B. Algorithm for MLS for EEG

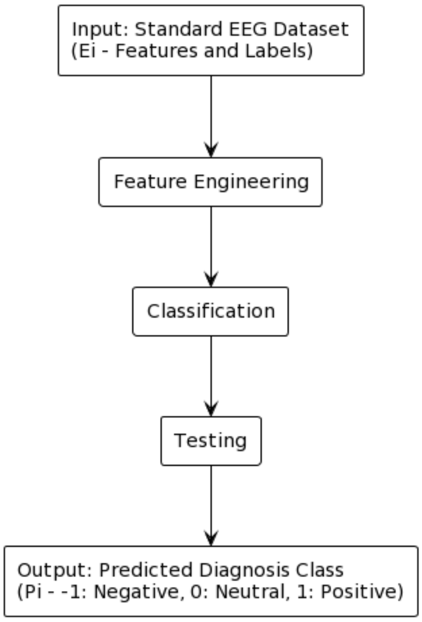

Fig 8. ML*S for EEG*

a. The method accepts a typical EEG dataset (Ei) as input, which consists of labels (the matching diagnostic classes) and features (data characterising the EEG signals).
b. Feature engineering is the stage when the input data is cleaned up and prepared for categorization.
c. The size of the feature data (Fz) and target data (Tz) is determined by the algorithm.
d. The approach uses a scaler transformation for each sample in the feature data to normalise the data and guarantee a balanced distribution across various diagnostic classes.
e. The subsequent phase of categorization receives the processed data.
f. The algorithm learns models to categorise the EEG data into several diagnostic classifications during this phase of classification.
g. Initialization is done on the parameters for ensemble model training.
h. To discover the ideal hyperparameters for the models, the technique use grid search optimisation.
i. The chosen hyperparameters are used to train the models.
j. By minimising the training loss, the method verifies the learned models.
k. Finally, a knowledge repository stores the learned models for further use.

l. Testing: In the testing step, the algorithm applies the learned models to brand-new, unstudied EEG data to make a diagnosis.
m. The algorithm is fed user test data.
n. The test data are subjected to feature engineering procedures comparable to those carried out in the preceding phase.
o. The loaded trained models from the knowledge repository.
p. Using the loaded models, the computer predicts the emotions of the EEG signals, classifying the precise emotion sentiment as either negative (-1), neutral (0), or positive (1).
q. Output: As a result of the method, the anticipated diagnostic class (Pi), which corresponds to the classes: -1 for Negative, 0 for Neutral, and 1 for Positive, is produced.

The technique uses feature engineering to process the input data, trains classification models, evaluates the models using fresh data, and then outputs the anticipated diagnostic class.

VI. Results and Discussion

A. *Experimental Result for FLS*

Table 2: Uncertainty in body temperature data

Input Membership Function Variable	Ranges (Deg. Cel.)	Output Membership Function Variable
Hypothermia	< 36	HS-1 (Health Score)
Normal	36-37.5	HS0
Light Fever	37.5-38	HS+1
Moderate Fever	38.1-38.5	HS+2
High Fever	38.6-39.5	HS+3
Very High Fever	39.6-42.5	HS+4

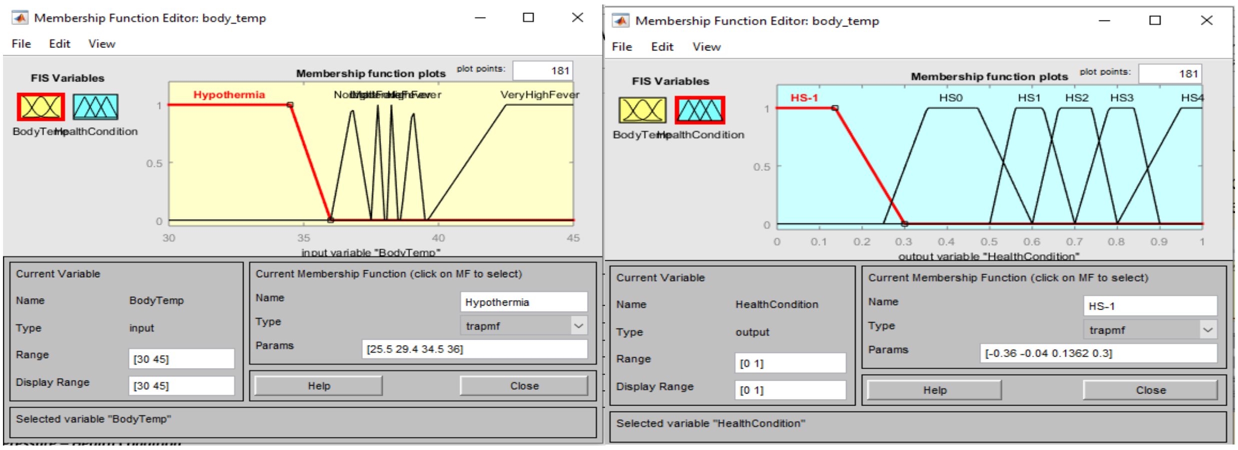

Fig 8: Body temperature membership function plot (input, output)

Table 3: Uncertain blood pressure data set

Input Membership Function Variable	Systolic Ranges (mm Hg)	Diastolic Ranges (mm Hg)	Output Membership Function Variable
Low	< 100	< 60	HS-1
Normal	100-120	60-80	HS0
Prehypertension	120-139	80-90	HS+1
Hypertension stage1	140-159	90-99	HS+2
Hypertension stage2	160-180	100-110	HS+3
Hypertension crisis	180-200	110-120	HS+4

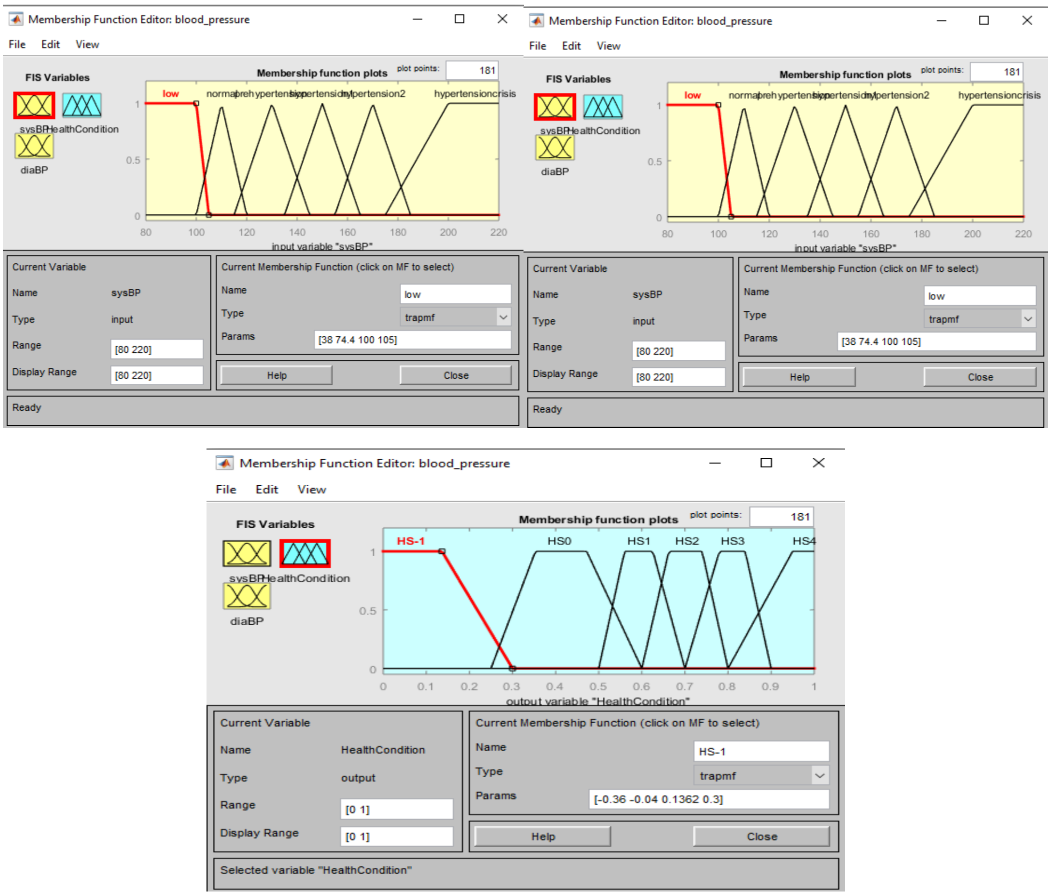

Fig 9: Blood pressure input, transformation, and output shown as a membership function

Table 4: Confused data sets for heart rate

Input Membership Function Variable	Ranges (beats per minute)	Output Membership Function Variable
Bradycardia	< 60	HS-1
Normal	60-100	HS0
Tachycardia	>100	HS+1

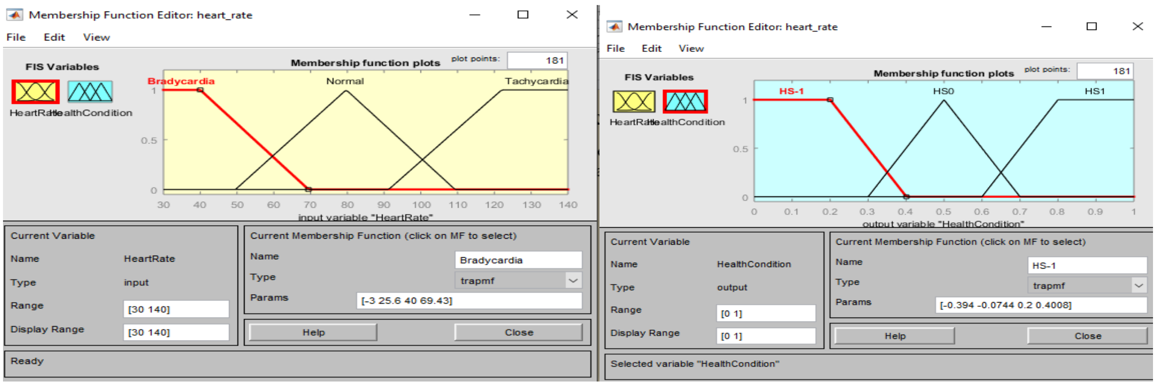

Fig 10: Heart rate input and output shown as a membership function

Table 5: Oxygen concentration data in a fuzzy collection

Input Membership Function Variable	Ranges (%)	Output Membership Function Variable
Normal	95-100	HS0
Mild Hypoxemia	91-94	HS+1
Moderate Hypoxemia	86-90	HS+2
Severely Hypoxemia	<85	HS+3

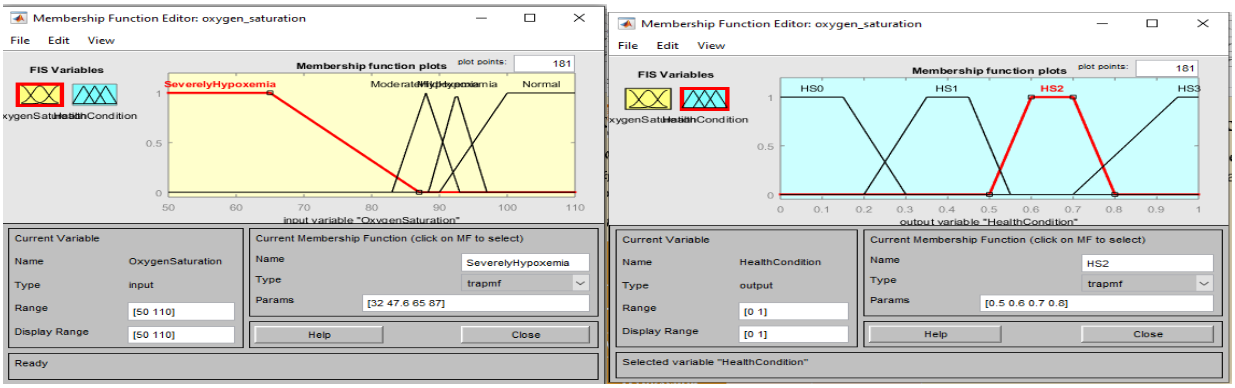

Fig 11: Oxygen input and output plot using the membership function

Table 6: Data on respiration rate is fuzzy

Input Membership Function Variable	Ranges (breaths per minute)	Output Membership Function Variable
Bradypnoea	<12	HS-1
Normal	12-20	HS0
Tachypnoea	>20	HS+1

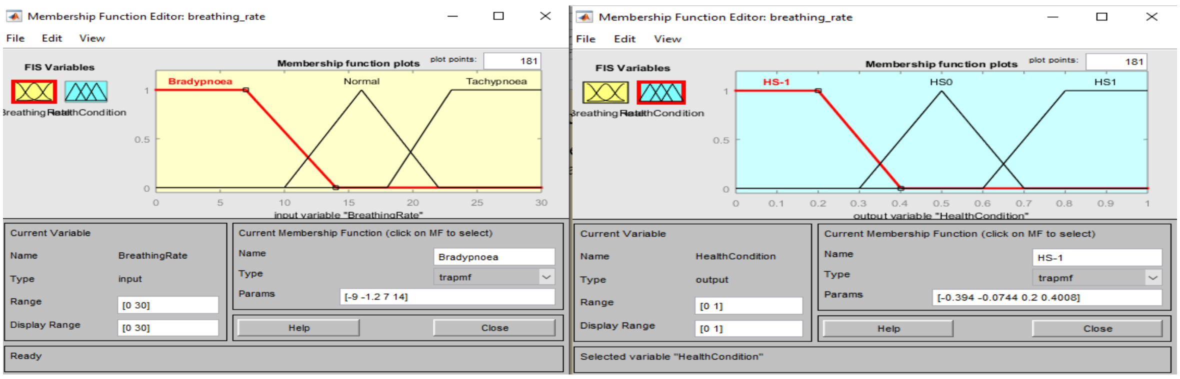

Fig 12: Breathing rate input versus output on a membership function plot

Table 7: Sugar level data with fuzzy sets

Input Membership Function Variable	Ranges (mg/dL)	Output Membership Function Variable
Poor	< 100	HS-1
Normal	100-140	HS0
Prediabetes	140-200	HS+1
Diabetes	>200	HS+2

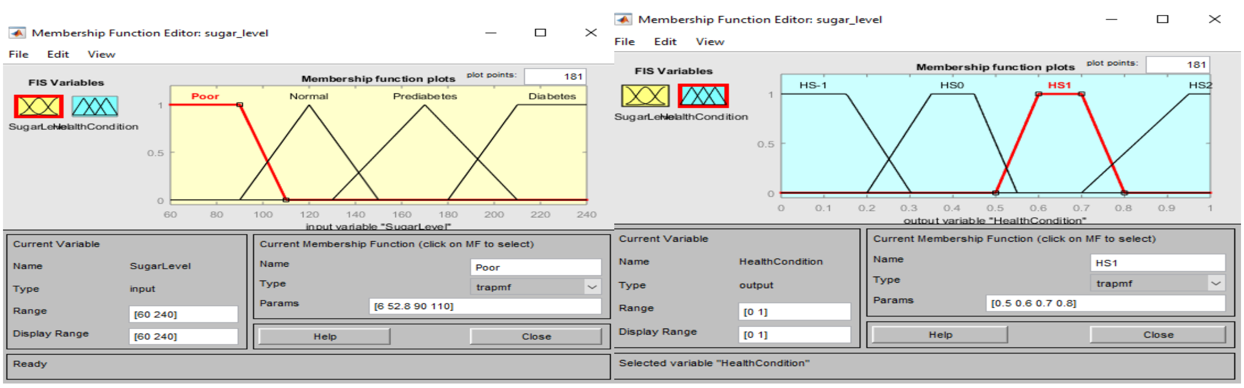

Fig 13: Input vs output sugar level visualisation using the membership function

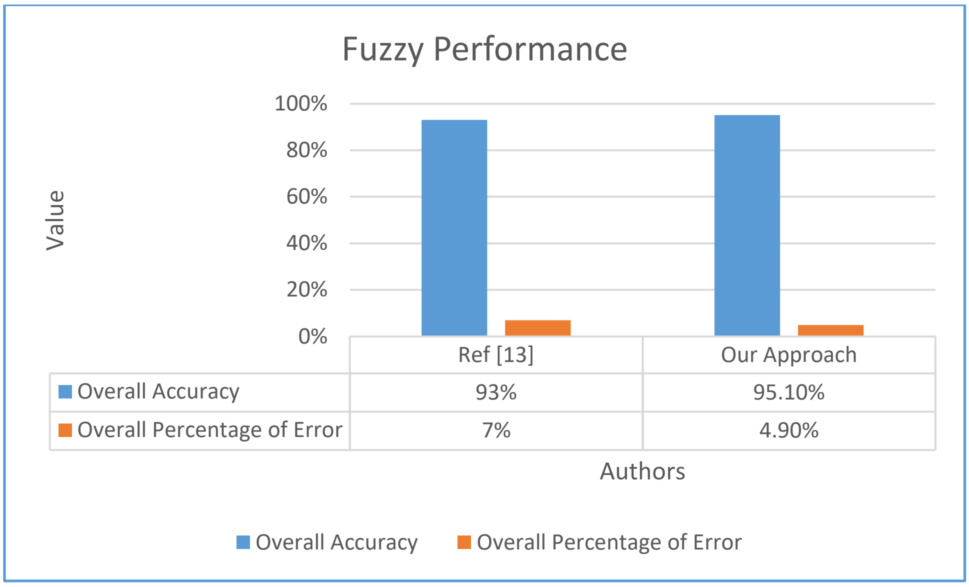

Fig 14: a diagram depicting a comparison

B. Experimental Result for MLS

The proposed MLS system is analyzed and evaluated on both ECG and EEG data classification based on standard benchmark datasets using confusion matrix statistical parameters used. Table 9 shows the performance parameters for ECG data classification of output labels class 0 to class 4.The class 0 outperforms better in all parameters as compared to other classes and class 3 has minimal performance as among all classes as shown in figure 14. The evaluation metrics, precision, recall and f-score performs better using XGBM as compared to GBM with maximum 0.98, 0.99 and 0.98 value.

Table 9: Performance Table of ECG Data Classification

Output Class	Precision		Recall		F-score	
	GBM	XGBM	GBM	XGBM	GBM	XGBM
class 0 (N)	0.95	0.98	0.99	0.99	0.97	0.98
class 1 (S)	0.94	0.96	0.22	0.26	0.36	0.40
class 2 (V)	0.76	0.80	0.76	0.81	0.76	0.79
class 3 (F)	0.44	0.48	0.23	0.28	0.30	0.35
class 4 (Q)	0.99	0.99	0.81	0.85	0.89	0.93

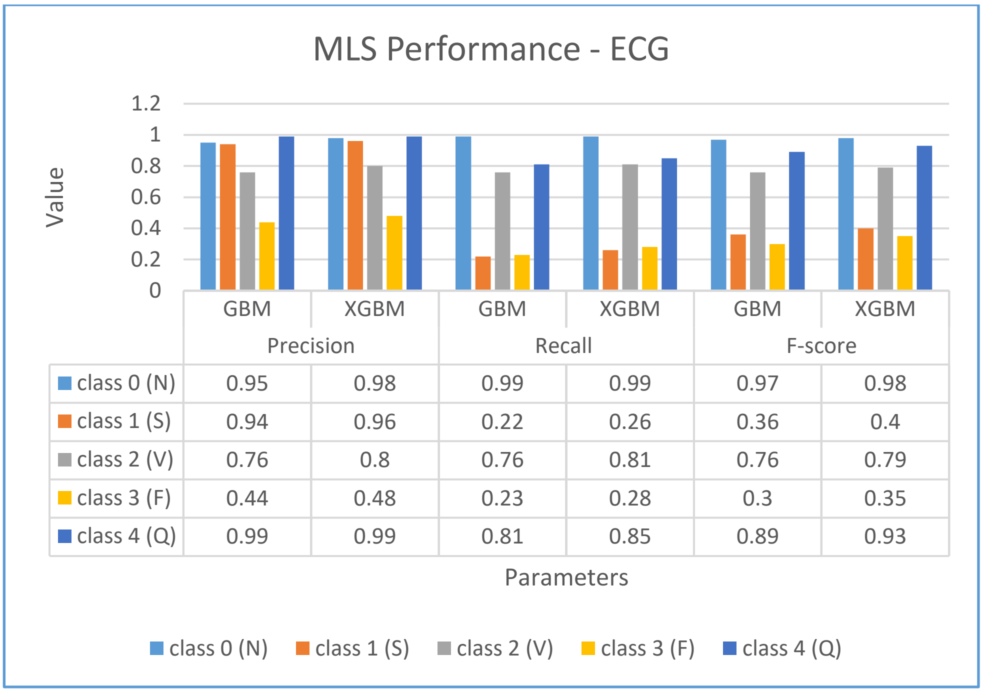

Fig 15: performance classification for ECG

The comparative analysis deals with accuracy parameters with existing researchers as tabulated in table 10. The proposed model accuracy is better with 0.985 as compared to other state of art models as shown in figure 15.

Table 10: Comparative analysis of ECG Data Classification

Parameter	Ref [51]	Ref [33]	Ref [30]	Our Work
Accuracy	0.958	0.941	0.962	0.985

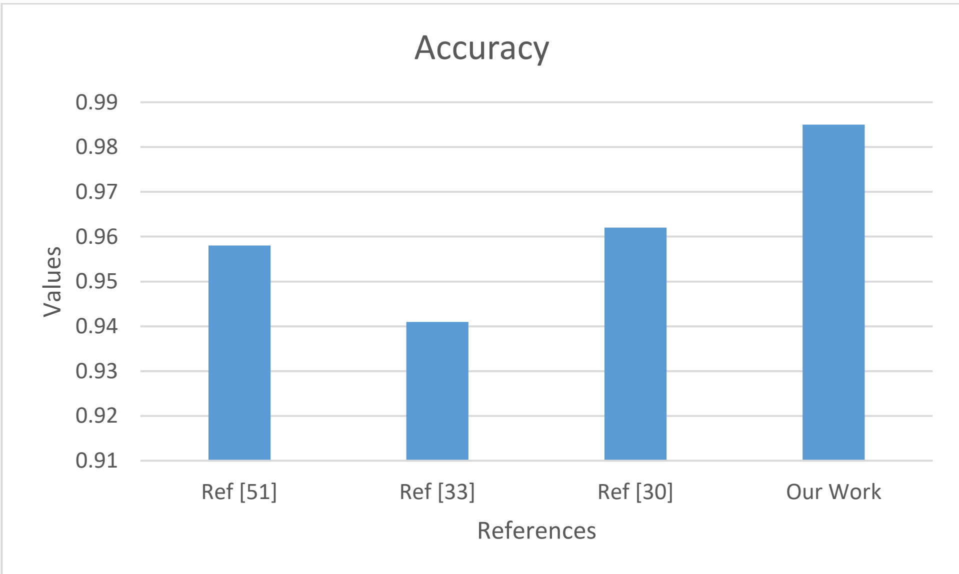

Fig 16: Comparative performance of various authors for ECG Data

Table 11 shows the performance parameters for EEG data classification of output labels class 0, class 1 and class -1. It is found that from both tables that XG Boost algorithm is superior than Gradient Boost algorithms as shown in figure 16.

Table 11: Performance Table of EEG Data Classification

Output Class	Precision		Recall		F-score	
	GBM	**XGBM**	**GBM**	**XGBM**	**GBM**	**XGBM**
Class -1	0.91	0.92	0.96	0.96	0.94	0.94
Class 0	0.91	0.93	0.29	0.31	0.36	0.44
Class 1	0.75	0.83	0.79	0.84	0.76	0.76

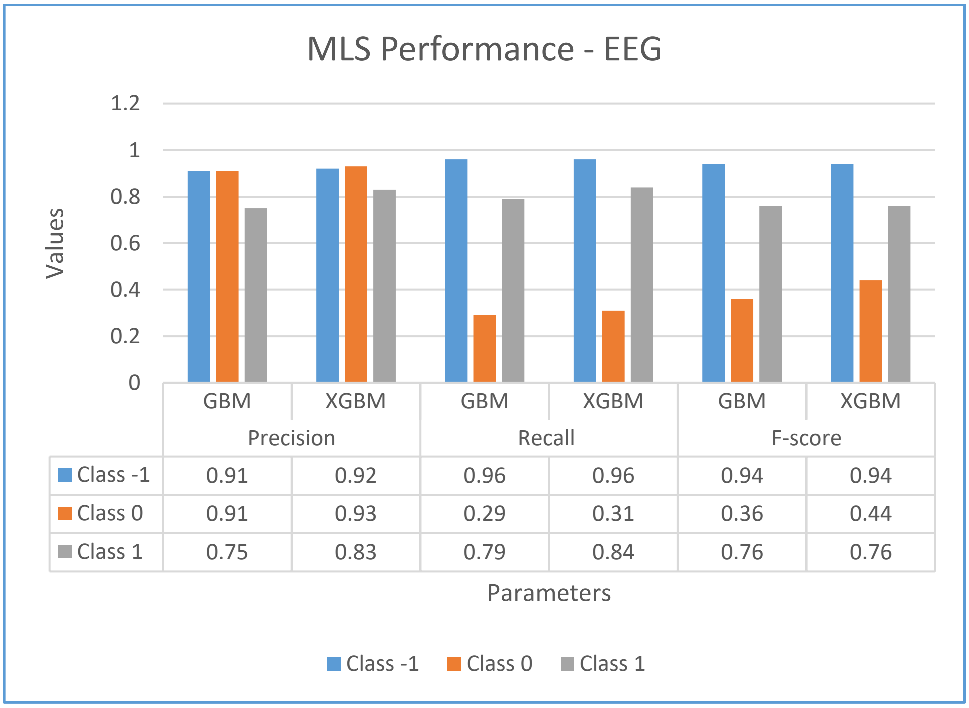

Fig 17: performance classification for EEG

The comparative analysis deals with accuracy parameters with existing researchers for EEG data classification as tabulated in table 12. The proposed model accuracy is better with 96% as compared to other state of art models as shown in figure 17.

Table 12: Comparative analysis of EEG based classification system

Parameter	Ref [37]	Ref [52]	Ref [39]	Our Work
Accuracy	88%	74%	92%	96%

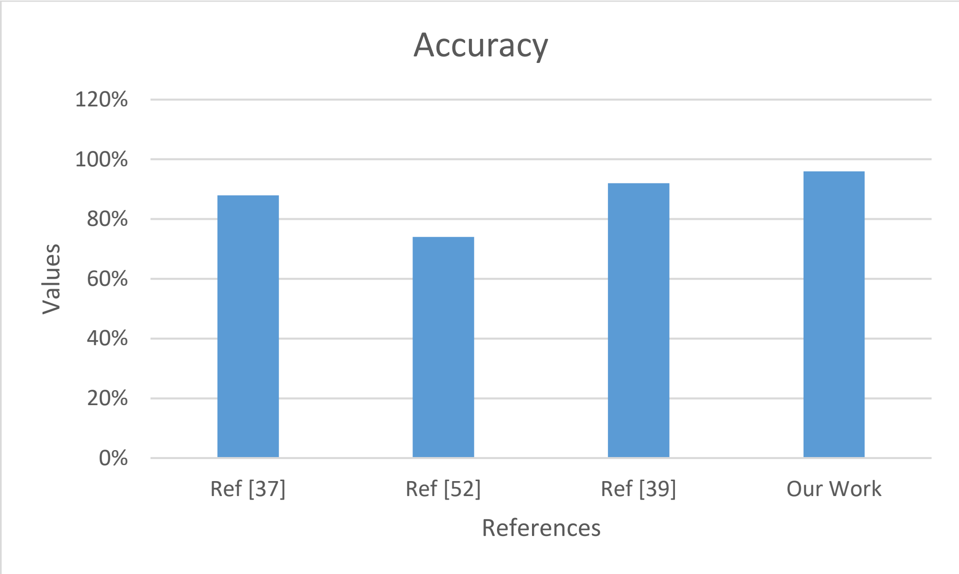

Fig 18: Comparative performance of various authors for EEG Data

VII. Conclusion

In conclusion, the Fog Enabled Intelligence Clinical Decision Support System (FICDSS), which combines fog computing with intelligent systems, represents a substantial development in healthcare applications. The FICDSS brings computational capability, real-time data processing, and intelligent decision support closer to the point of care by utilising the advantages of fog computing. The analysis and interpretation of patient data are improved by the application of intelligent systems, including as machine learning, fuzzy logic, and expert systems, resulting in more precise and fast clinical decision-making. FICDSS has a number of advantages in the healthcare industry, including better patient outcomes, a decrease in medical mistakes, and optimal resource use. Healthcare practitioners may make wise judgements, see warning signals, and act quickly using real-time and context-aware decision assistance. The FICDSS also permits telemedicine and remote monitoring, expanding access to healthcare services outside of conventional venues. The FICDSS's implementation is not without difficulties, though. Important factors in the adoption of FICDSS include privacy and security issues, the interoperability of various healthcare systems, and the necessity for strong regulatory frameworks. Healthcare providers, technology creators, legislators, and other stakeholders must work together to address these difficulties. Future research and development will be required to improve the capabilities of FICDSS. This entails improving the clever algorithms, including other data sources, and regularly updating the databases of medical knowledge. Additionally, it's important to carefully consider how utilising FICDSS would affect issues of accountability, openness, and justice. In conclusion, by offering intelligent, context-aware decision assistance at the point of care, the Fog Enabled Intelligence Clinical Decision assistance System (FICDSS) offers enormous potential to improve healthcare. The FICDSS provides new prospects for optimising patient care, enhancing healthcare outcomes, and developing the area of intelligent healthcare systems by merging the capabilities of fog computing with intelligent systems.

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