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A Novel Scheme for Classification of Epilepsy Using Machine Learning and a Fuzzy Inference System Based on Wearable-Sensor Health Parameters

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Abstract: The tremendous growth of health-related digital information has transformed machine learning algorithms, allowing them to deliver more relevant information while remotely monitoring patients in modern telemedicine. However, patients with epilepsy are likely to die or have post-traumatic difficulties. As a result, early disease detection could be essential for a person's survival. Hence, early diagnosis of epilepsy based on health parameters is needed. This paper presents a classification of epilepsy disease based on wearable-sensor health parameters that use a hybrid approach with ensemble machine learning and a fuzzy logic inference system. The ensemble machine learning classifiers are used to predict epilepsy events using ensemble bagging and ensemble boosting regression. The experimental results show that compared to the ensemble bagging classifiers and other state-of-the-art methods, the ensemble boosting classifier with the fuzzy inference system outperformed with a 97% accuracy rate.

Keywords: healthcare; machine learning; epilepsy; fuzzy logic inference system; telemedicine

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Citation: Kadu, A.; Singh, M.; Ogudo, K. A Novel Scheme for Classification of Epilepsy Using Machine Learning and a Fuzzy Inference System Based on Wearable-Sensor Health Parameters. *Sustainability* **2022**, *14*, 15079. https://doi.org/10.3390/su142215079

Academic Editors: Ripon Kumar Chakrabortty and Andreas Kanavos

Received: 2 October 2022
Accepted: 9 November 2022
Published: 14 November 2022

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1. Introduction

With the need for guaranteed precision in intricate events and the cumulative demand for healthcare services, it is obvious that machine learning (ML) is crucial to the operation and use of technology. Increasing productivity while meeting healthcare requirements, allotting time, and automizing hospital logistics is necessary. The main objectives of telemedicine are to minimize waiting times, lower costs, and close communication and accessibility gaps in the medical sector. Healthcare services utilize telehealth to address demand versus supply mismatch issues using information and communication technology (ICT) methods. Machine learning may help with this difficulty by creating algorithms that match the accessibility of healthcare experts with acceptable clinical skill sets in the nearby area. Many countries' average life expectancy has significantly increased due to improved healthcare systems. Technology that addresses older people's issues can allow them to be independent and receive top-notch care. Epilepsy is a significant issue that older adults face. An older adult who falls may suffer severe injuries and develop other, frequently significant, health issues. Additionally, falling and losing your equilibrium could be indicators of a condition that could be fatal. Therefore, the injured person must obtain urgent medical care after a fall, regardless of what caused it. Patients frequently need emergency medical attention because they cannot stand independently [1–7].

Most of the existing work has built its methodologies for disease diagnosis based on health parameters using machine learning and deep learning algorithms, mainly based on audio signals, time-series data, and image data. For audio signals, heart, respiratory, and inhaler sounds are used, whereas for time-series data, ECG, EEG, and PPG signals are used within a self-experimentation setup. Then, the results are analysed using performance parameters such as accuracy, MAE, sensitivity, specificity, precision, recall, f-score, and evaluation time. Still, the results of epilepsy diagnosis are not satisfactory, and the use of a deep learning model causes high computation time with higher GPU requirements to process the data. In addition, acquisition of time-series data like ECG, EEG, and PPG requires more precision and time to create the best-supervised data.

Most researchers have created systems for health monitoring and diagnostics employing cutting-edge technologies. IoT is utilized to transmit real-time data about medical parameters. Many soft computing methods are employed for classifying health conditions, including machine learning, deep learning, and fuzzy logic. Machine learning has advantages over other algorithms when it comes to soft computing. This study's primary goal is to examine ML's practical applications, such as treatment planning, diagnosis, prevention, and case identification of high-risk patients. To help hospitals run more efficiently and reduce physician workload, finding a tool for artificial diagnosis that can be applied in real-world settings is essential. ML addresses high-risk populations, including the elderly, diabetics, hypertensive patients, pregnant women, asthmatics, cancer patients, and post-transplant patients, which is crucial in terms of urgency.

Automating the diagnostic process by providing an intelligence model will assist clinicians and doctors in making the best diagnosis decision possible. A hybrid model consists of ML and a fuzzy inference system (FIS) for evaluating health scores and status. Input is given to the ML system, which provides the precision output ranges from 0–1. Regression-based variable output of the ML is given to the FIS as input to identify the state of disease as 1-normal, 2-mild, or 3-severe, as shown in Figure 1. The output of the FIS depicts health status based on the classifications. Input sensor data is given to the ML system, which provides the precision output ranges from 0–1. The regression-based variable output of the ML system is given to the FIS system as input to identify the state of disease as 1-normal, 2-mild, or 3-severe, as shown in Figure 1. The output of the FIS depicts health status based on the classifications. Additionally, proposed machine learning models have an advantage over deep learning models in that they are easy to build and make better predictions with supervised human interaction. On the other hand, deep learning models are difficult to build as they use complex, multi-layered neural networks. The advantage of fuzzy logic systems is that knowledge gradually turns into wisdom and can be used as a decision-making tool. Considering the proposed IoT ecosystem with the added benefits of an intelligent model and the use of wearable sensing technology to monitor health parameters for epilepsy diagnosis, the proposed approach's primary contributions include:

- Designing a diagnosis decision-making assistance system that incorporates two modalities;
- Development of a new classification system for epilepsy identification based on routinely monitored health indicators;
- A new and improved diagnosis technique based on machine learning and fuzzy logic, as well as the novel idea of incorporating sensor data.

This paper is structured as follows: Section 2 shows the related work, and Section 3, materials and methods, shows the implementation of the experimental method and evaluation parameters. Then, the experimental results and discussion are described in Section 4. Finally, the conclusion is given in the last section.

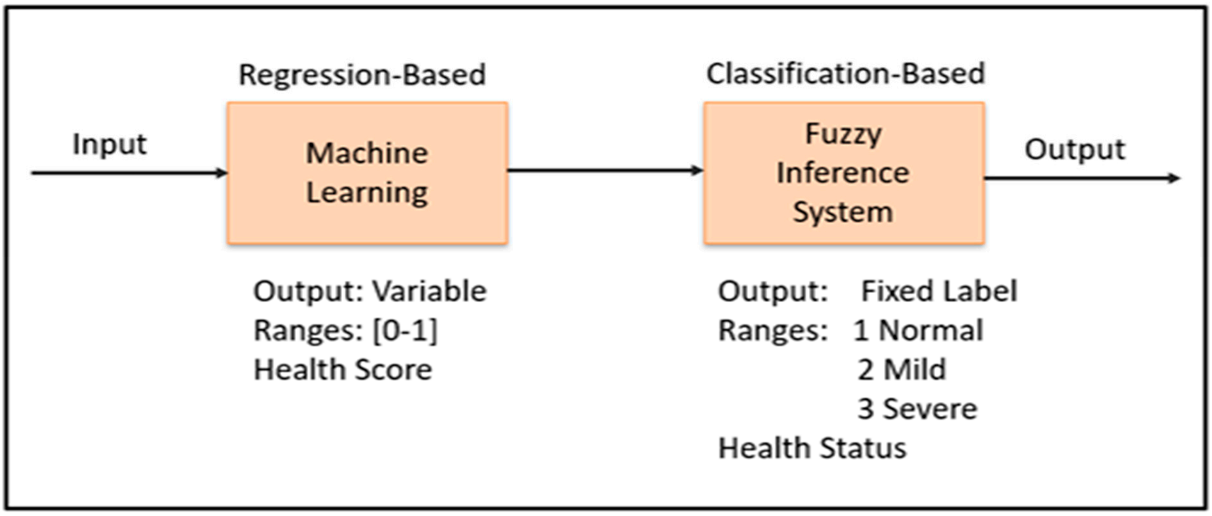


Figure 1. Hybrid intelligent model.

2. Related Work

Various existing works have been published on implementing epilepsy disease diagnosis based on various intelligent techniques. A ubiquitous system was designed to track COVID-19 patients' physical and psychological states inside and outside a hospital setting [8]. A novel data fusion approach has been suggested based on type-2 fuzzy logic [9]. The author created a novel prognostic model for health data storage to suit patient demands and ensure quick decisions in [10]. Effective data analytics based on sensed data for monitoring and evaluating patients in real time to assist medical and hospital personnel was incorporated in [11]. A precise categorization technique for heart sound diagnosis has been provided [12]. Internet of Medical Things (IoMT)-based healthcare monitoring systems have been suggested, developed, and subjected to fuzzy logic-based artificial intelligence analysis [13]. A low-cost, high-quality, versatile, wearable smart device was designed to track fitness athletes and patients with heart disorders in the healthcare system [14]. An innovative and intelligent healthcare system has been created based on cutting-edge innovations like ML and the Internet of Things (IoT) [13,15]. A suggested IoT-based healthcare infrastructure would offer patients remote monitoring in an emergency [16]. A planned indoor/outdoor information system is based on the IoT [17]. Using deep residual networks (ResNets) and the optimal S-transform (OST), a unique technique for identifying wheeze, crackle, and normal sounds has been described [18]. A telemedicine platform has been developed with an intelligent diagnosis decision-support system [19]. The seamless interface between BCI and IoT devices has been suggested using an expanded PSO-NN [20]. A framework allows caregivers to obtain data on the temperature and pulse rate of those being watched at home [21]. A proposed approach improves a cloud-based fitness healthcare system [22].

The integration of fuzzy logic systems and algorithms has been presented in several studies [23]. The researcher creates a theoretically robust model to support informed decision-making that predicts patients' happiness with telemedicine in [24]. Using the partly observable Markov decision process (POMDP) to simulate heart disease prediction has been suggested [25]. The system's design, implementation, first testing, and analysis are shown in [26]. Patients utilizing a Diskus dry powder inhaler were recorded using the Inhaler Compliance Assessment device [27]. A system with a scalable design that can track thousands of older people, spot falls, and alert caretakers is shown in [28]. The proposed system employed machine learning to choose a medical specialty based on a patient's combined illness symptoms [29]. The benefits of several specific medical imaging applications have been explored [30]. Each breath cycle was automatically divided into smaller cycles and calculated using a threshold in [31]. These data can be used to know the present decision-making stage [32]. An integrated approach combines the IoT and the fuzzy inference system (FIS) to deploy intelligent illness diagnostics to identify various diseases [33]. The Smart Healthcare Management Evaluation (SHME-FDM) technique was suggested to evaluate the effectiveness of technology integration [34]. For precise illness prediction, a novel regression and classifier method using the generalized fuzzy intelligence-based ant lion optimization (GFIbALO) method has been suggested [35]. TrueImage, an automated image evaluation system with a machine learning pipeline, was presented to identify subpar dermatological photographs and assist patients in obtaining better pictures [36]. An Intelligent Diabetic Assistant (IDA.) is a suggested prototype for an autonomous system that determines the priority of treatment and diagnosis based on observations on the screen [37]. A brand-new approach to automated DR diagnosis uses cloud computing and artificial intelligence [38]. One author used the GBDT to forecast the blood pressure rate, considering physiological data gathered by the EIMO device [39,40].

Author [41] presented a lookup table to investigate EE and SE issues that enabled a fuzzy-based system and accomplished a successful symmetric trade-off to improve overall system performance in 5G networks and achieve optimum results. The main focus in [42] is on finding unfamiliar nodes in the 3D environment and proposed the implementation of APPA algorithm work to find the exact location of the nodes. Author [43] worked on three scenarios, Echelon 1, 2, and 3, to investigate different system parameters. The proposed model consumes energy and provides a better-normalized, achievable performance than a conventional model. The proposed system was simulated in NS-2 and Matlab. Using variational data assimilation, an epidemiological model for forecasting and policy evaluation is provided in [44]. It includes fresh data in real time. It is suggested in [45] to merge several sources of temporal information using a sequential network-updating strategy based on data assimilation techniques.

3. Materials and Methods

3.1. Experimental Method

We proposed a block diagram with a hybrid framework (EMLR-FLIS) considering ensemble machine learning regression (EMLR) with a fuzzy logic inference system (FLIS), as shown in Figure 2 below. Health records from wearable sensors were recorded to create standard health data for machine learning training and testing. Raw data were transformed into advanced features through feature engineering, which were then segregated into train and test feature sets. For creating a trained model, machine learning modelling was performed on the train feature set. The health score was first applied to the fuzzy inference system as a predicted output to determine the patient's health state.

3.1.1. Wearable Sensor Health Record Dataset

This dataset includes standard clinical records concerning epilepsy patient health behaviour and has the following health attributes, shown in Table 1.

Table 1. Health Attributes for Epilepsy Patients.

Input	Measures in	Output
Air quality	Parts per million (PPM)	
Body acceleration	Three-axis motion records	
Respiratory rate	Breath per min	Health score
Heartbeat rate	Beats per minute (BPM)	(Regression-based value)
Oxygen level in blood	Percentage (%)	
Body temperature	Degrees Celsius (°C)	

This dataset was acquired and considered under expert guidance. The proposed data were a compilation of health sensor values (as mentioned in the table) for a hundred volunteers collected daily, living for certain hours under simulated conditions. The mean value of experimentation for a single day was treated in a dataset for a hundred participants using a data logger on a cloud service platform based on IoT.

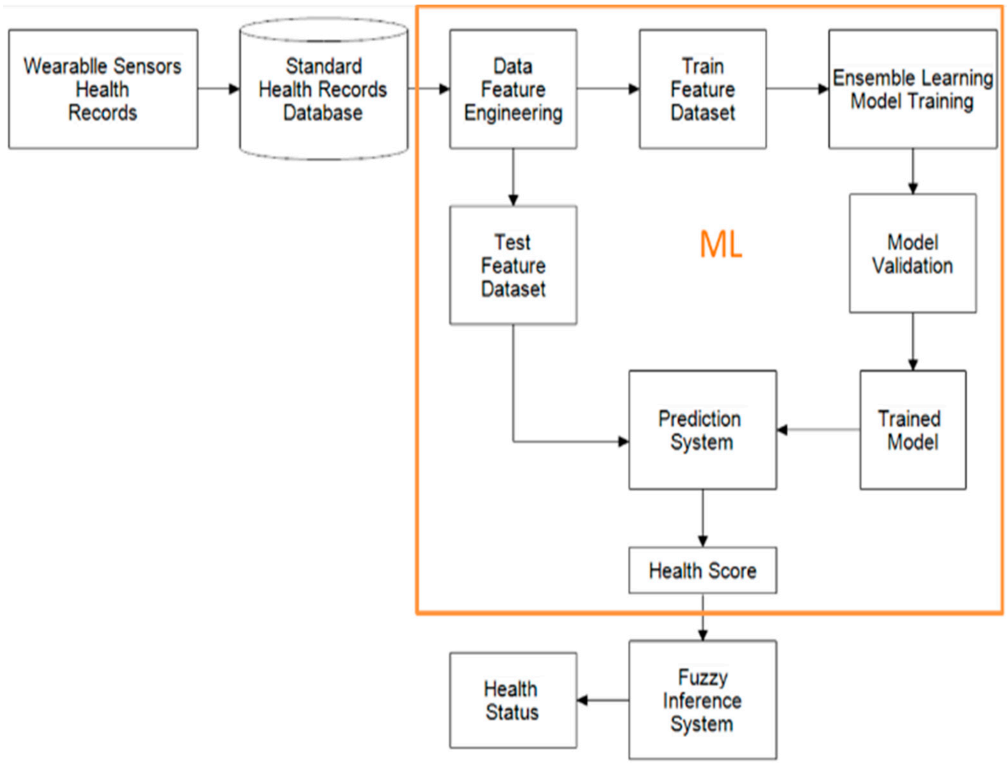


Figure 2. Proposed intelligent framework using EMLR-FLIS.

3.1.2. Data Feature Engineering

Feature engineering selects, manipulates, and transforms raw data into features used in supervised learning. For effective model learning, developing and enhancing features may be crucial. It can provide new features to streamline and speed data transformations while improving model correctness. Data transformation, missing data value checking, and data scaling are all performed in feature engineering. Data transformation converts raw data into a format more appropriate for the model or algorithm and for general data discovery. It is an essential step in the feature engineering process that facilitates insight gathering.

3.1.3. Ensemble Machine Learning Model Training and Validation

A regression-based analytics system examines the relationship between independent variables or features and a dependent variable or result. Ensemble learning is a meta-method that utilizes the predictions from various models to enhance classification performance. It is a technique for predictive modelling in machine learning, in which an algorithm is used to forecast continuous results for the classification of health data in terms of a health score, which indicates "how comfortable a person has after epilepsy". A regression model based on ensemble learning, which employs ensemble bagging and ensemble boosting, is used in the proposed approach. The bagging method uses the average predictions from multiple trees of the decision model mapped to various sets of dataset samples. A weighted average of the predictions is produced by boosting, which entails sequentially adding ensemble members that correct the predictions provided by earlier models. The random forest bagger regressor is used in bagging, and the AdaBoost regressor is used in boosting. The output of a machine learning-based regressor is categorized into severity categories for epilepsy ranging from 0 to 1.

- In ensemble bagging algorithms, suppose m represents all the data's characteristics. Then, the following points are incorporated to provide the learning model.

Step 1: Build a decision tree connected to the specific sample data points by selecting k number of features at random from m features of data such that k $\ll$ m from the training data;

Step 2: Find the optimal split for the k features that were chosen;

Step 3: Use the optimal split to divide the node into child nodes;

Step 4: Continue until you reach the leaf node;

Step 5: Repeat this process until you have a forest of trees. Then, for new data points, locate each decision tree's predictions, and allocate the latest data points to the category that receives the most votes. For example, in the case of classification trees, predictions could be made based on the majority of votes if B is bagging from Equation (1) as shown below:

$$f = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \tag{1}$$

- In ensemble boosting algorithms,

Step 1: Initialize the dataset and give each data point the same weight. The initial weighting can be determined by Equation (2):

$$\omega = 1/N \in [0,1] \tag{2}$$

where N indicates the total number of data points and the number of records;

Step 2: Give the model this as input and find the data points that are incorrectly categorized. The actual influence is categorizable using Equation (3) as follows:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1 - TotalError}{TotalError}\right) \tag{3}$$

where alpha indicates the weight that each stump had in the final judgment; the total error is the number of misclassified data;

Step 3: 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 Equation (4) is used:

$$\omega_i = \omega_{i-1} * e^{\pm a} \tag{4}$$

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.

3.1.4. Fuzzy Logic Inference System and Predicted Output

A fuzzy inference system infers the values in the input vector of the health score, and based on some rules, grants values to the output vector in terms of normal, mild, and severe health conditions. The degree to which a proposition is true depends on fuzzy logic. The process flow of the fuzzy logic inference system is shown in Figure 3. The input and output health parameters as crisp input and output are defined as fuzzy input and output sets. The fuzzy logic technique to map a given input to output is known as fuzzy inference. The inference engine applies fuzzy rules from the knowledge base and produces the fuzzy output.

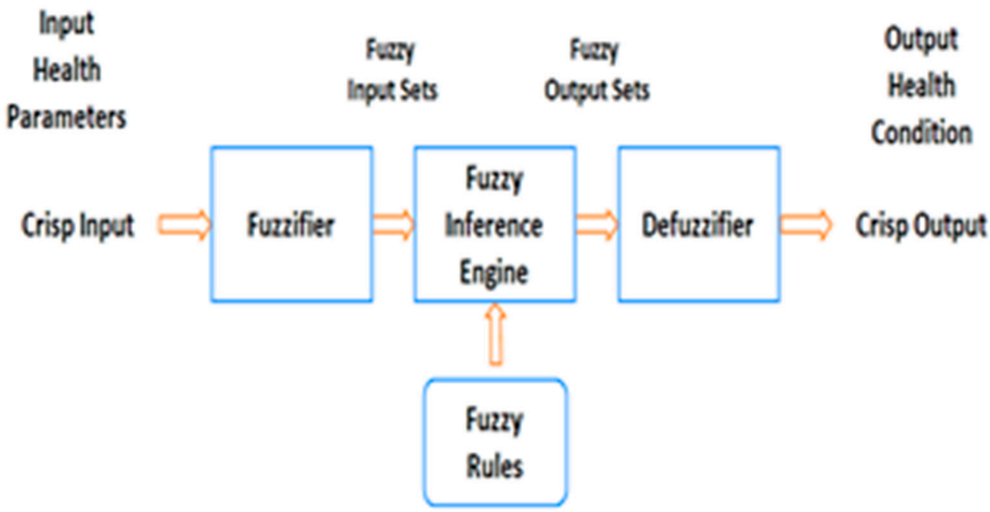


Figure 3. Process diagram of fuzzy logic inference system.

3.2. Experimental Procedure

The proposed experimental system, as it appears in the figure presented to accomplish WBANs, depends on the technologies of IoT devices and the embedded or wearable WBANs. In this framework, WBANs accumulate data and send them to the controller unit, which can support interpreting the information received. Furthermore, these devices are programmable and can be associated with the internet. Again, unlike sensor networks, they have no energy impediments and are connected directly to power. To this end, a proficient, intelligent approach and computational hardware are utilized.

In the proposed experiment, a supervised machine-learning approach was used. The controller unit for expert knowledge generates the anomaly events. The framework is primarily categorized in three layers, as described in Figure 4. The wearable device consists of a microcontroller-based system to which wearable sensors interface in order to monitor health parameters such as air quality, body acceleration (3-axis records), respiratory rate, heartbeat rate, oxygen level in the blood, and body temperature using MQ 135, ADXL335, MQ2, MAX30100, and DS18B20 sensors (Winsen Electronics, Hong Kong).

3.3. Experimental Algorithms

3.3.1. Algorithm for Machine Learning System

- Input: Ei- Standard benchmark Wearable Sensor Health Parameter Dataset with features and labels
- Output: Predicted disease health score class
- Pi- Regression-based value [0–1]
- Procedure:

1. Feature Engineering

   Step 1: Determine the size of feature data and target data, Fz, Tz
   Step 2: For in range of Fz

Apply scaler transformation to each sample
Data normalization with equal distribution for each class
end

2. Classification

   Step 3: Initialize parameters to train MLR models
   Step 4: Find hyperparameters of the trained model using grid search optimisation
   Step 5: Train the model based on best-selected hyperparameters
   Step 6: Validate the model by obtaining a training loss minimum
   Step 7: Store the trained model in the knowledge repository Testing

Step 8: Load user test data
Step 9: Apply feature engineering from steps 1 to 3
Step 10: Load the trained model from step 8
Step 11: Predict the health score of health parameter data to get a precise health score.

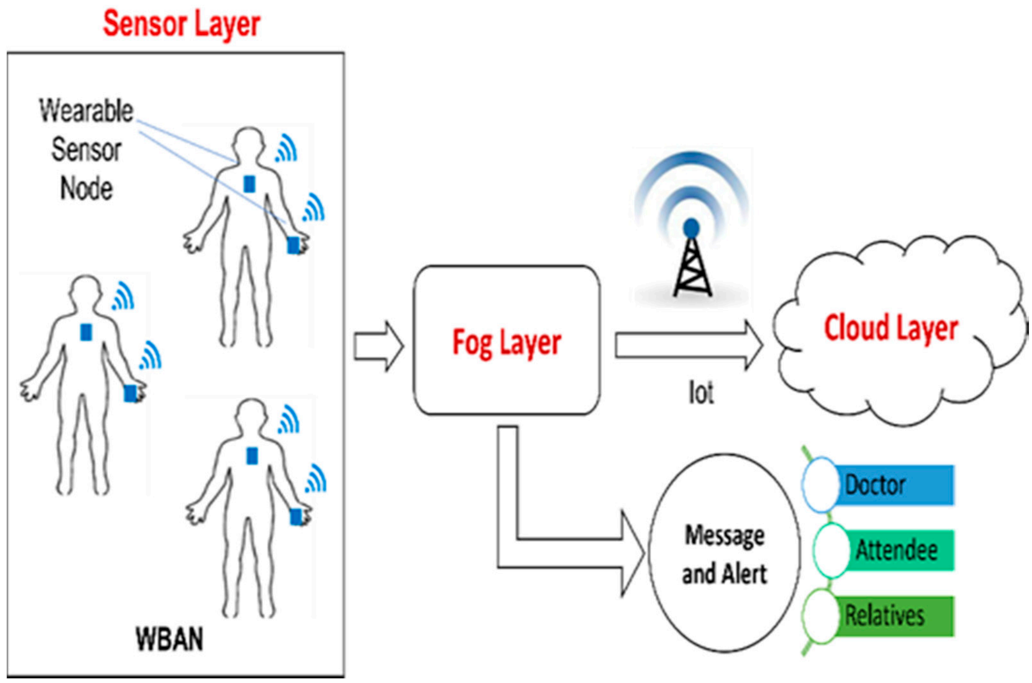


Figure 4. Proposed framework.

3.3.2. Algorithm for Fuzzy Inference System

- Input: Wearable or non-wearable biomedical sensor value
- Output: Predictive label or response
- Procedure:

Step 1: Define linguistic variables and terms used to describe health metrics
Step 2: Build the membership function for it
Step 3: Define the knowledge rule base
Step 4: Fuzzification: The membership function converts crisp facts to fuzzy variables
Step 5: Inference engine: Analyse the rule-based model and combine the results of each rule
Step 6: Defuzzification: Conversion of output data to values that aren't fuzzy

3.4. Evaluation Parameters

The confusion matrix, which displays the number of correctly and incorrectly classified cases by event type, is where the classification efficiency measure is generated from (normal vs abnormal). As a result, several statistics-based measurements are evaluated and used as the basis for comparative classifier analysis. Various performance measurements that evaluate a classifier's performance are presented using the metrics mentioned. The most-often employed measures are RMSE, accuracy, precision, recall, f-score, sensitivity, and specificity. True positive (*TP*), true negative (*TN*), false positive (*FP*), false negative (*FN*), and receiver operating characteristic (*ROC*) are the main parameters that define the performance of an algorithm and are calculated by using Equations (5)–(12):

$$Accuracy = (TP + TN) \ / \ (TP + TN + FP + FN) \quad (5)$$

$$Precision = TP \ / \ (TP + FP) \quad (6)$$

$$Recall\ /\ Sensitivity = TP\ /\ (TP + FN) \tag{7}$$

$$Specificity = TN\ /\ (TN + FP) \tag{8}$$

$$F - score = 2\ *\ TP\ /\ (2TP + FP + FN) \tag{9}$$

$$Negative\ Predictive\ Value\ (NPV) = TN\ /\ (TN + FN) \tag{10}$$

$$False\ Positive\ Rate\ (FPR) = FP\ /\ (FP + TN) \tag{11}$$

$$False\ Negative\ Rate\ (FNR) = FN\ /\ (FN + TP) \tag{12}$$

4. Results and Discussion

The proposed system was implemented in PyCharm software with Anaconda Distribution. The proposed system was evaluated in three phases: training, validation, and testing. The dataset samples were split randomly for each phase into 60%, 15%, and 25% of the total dataset samples for the training, validation, and test phases, respectively. Based on this, the system performance was evaluated based on a confusion matrix and statistics. A sample of the patient's report was produced on the server once sensor data was received and sent via a smart device. Patient sensor data and patient symptoms in terms of health score make up the report's three sections. People who live in rural areas can utilize the suggested system as an efficient and low-cost option to assess whether they have experienced a severe health issue and, if so, seek care from a hospital. The statistical health record histogram plots with input and output parameters are shown in Figure 5. It shows that there are a total of eight input parameters and two output parameters available in the dataset. The first eight histogram plots show the variation of input sensor data values.

In addition, output classification data histograms of health scores were classified 1, 2, and 3 as normal, mild, and severe, respectively, as shown in Figure 6. The majority of the output classifications were from the normal category, 54.44%, and the other two output categories, mild and severe, had 19.35% and 26.21%, respectively.

Initially, ensemble regression-based algorithms, bagging, and boosting were trained and validated as per the procedure explained in the proposed work. Later, performance was evaluated and analysed for both algorithms. The predicted data from the proposed model were compared with the ground truth classification data, i.e., actual classification data, and plotted the relationship between them, as shown in Figures 7 and 8. It has been observed that the proposed system is able to predict the exact data as compared to ground truth data.

Mean squared error and accuracy were evaluated for both algorithms as described in Table 2 and graphically represented by Figure 9. The better performance was powered by the ensemble boosting algorithm at 0.99, as compared to the bagging algorithm.

Table 2. Performance of Regressor Algorithm.

Parameters	Ensemble Bagging	Ensemble Boosting
RMSE	0.02	0.01
Accuracy	0.98	0.99

After successfully training, validating, and testing regression algorithms, the proposed system was further analysed to assess the overall system performance for the regression algorithms. The confusion matrix of the proposed test structure for both systems is shown in Figure 10. It shows the relationship between actual and predicted output. Most of the samples were correctly categorised and shown diagonally in colour; only a few samples were misclassified and shown non-diagonally.

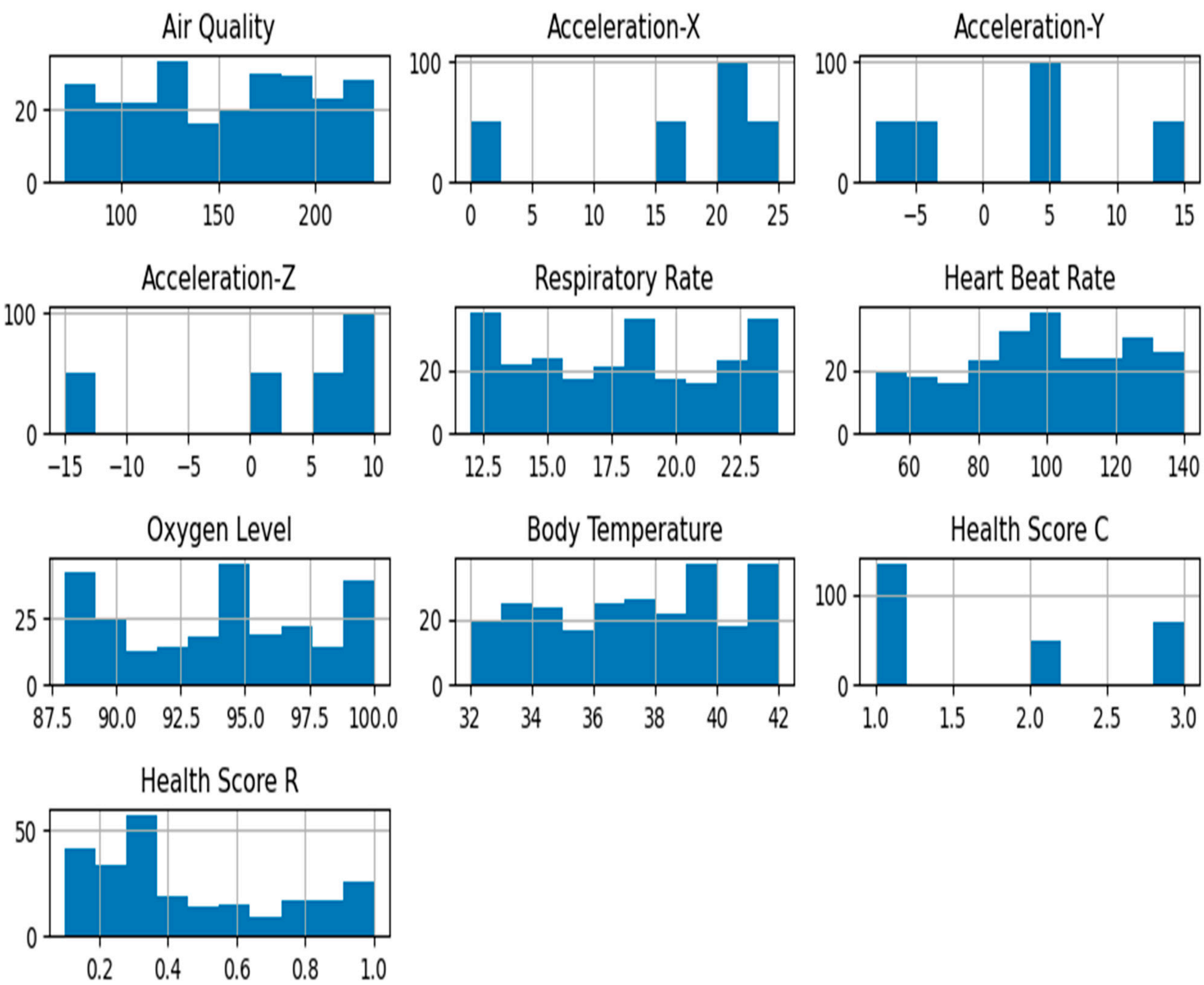


Figure 5. Output classification data histograms.

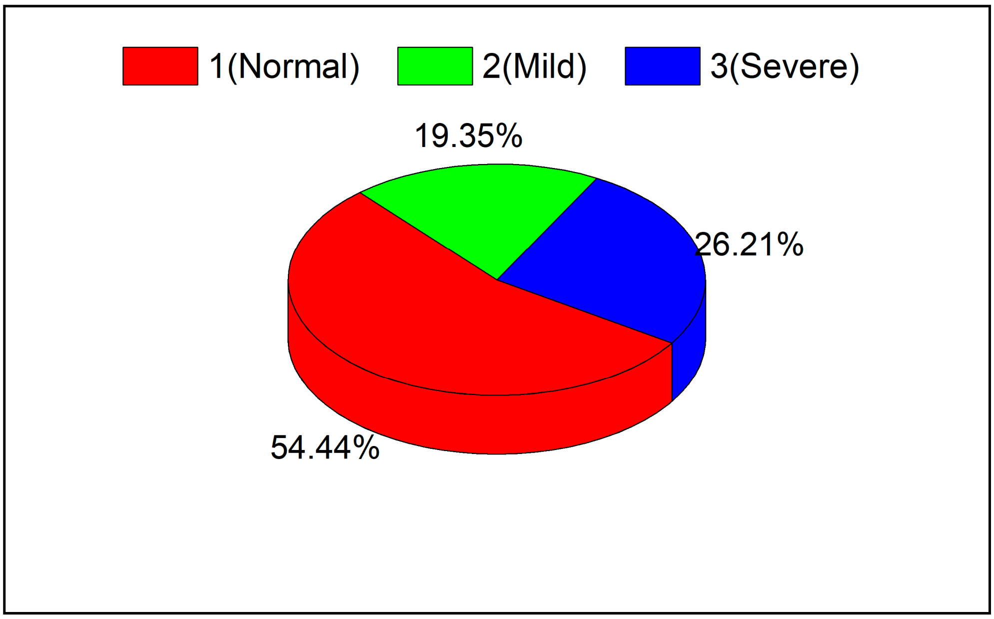


Figure 6. Count of classification data.

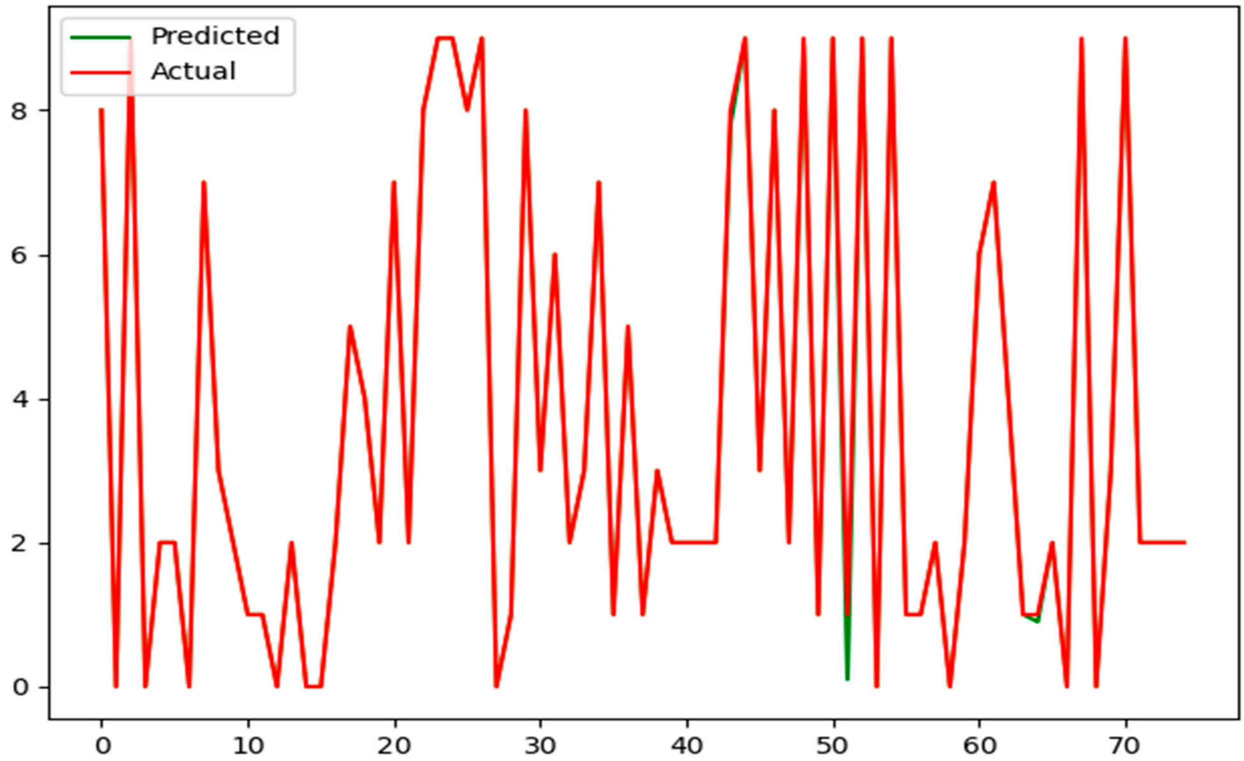


Figure 7. Predicted vs. actual (ground truth) output nature using bagging regressor.

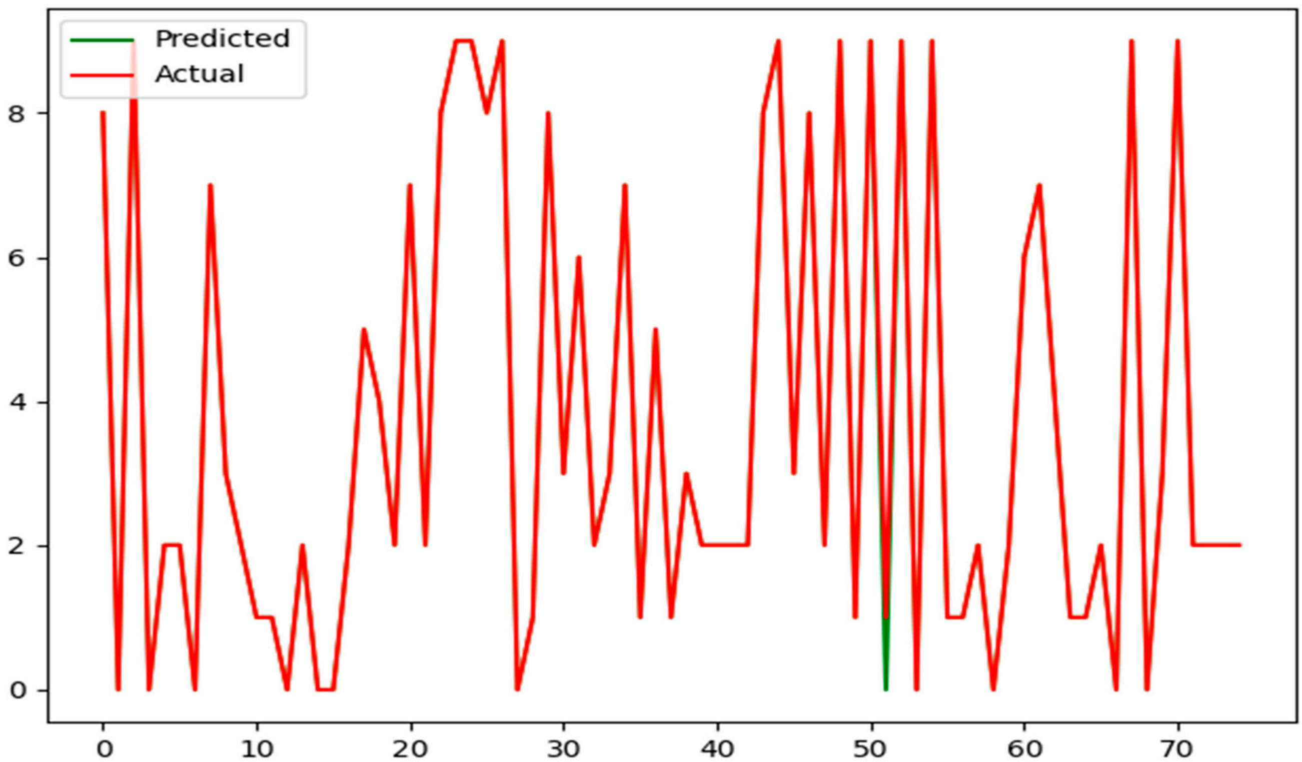


Figure 8. Predicted vs. actual (ground truth) output nature using boosting regressor.

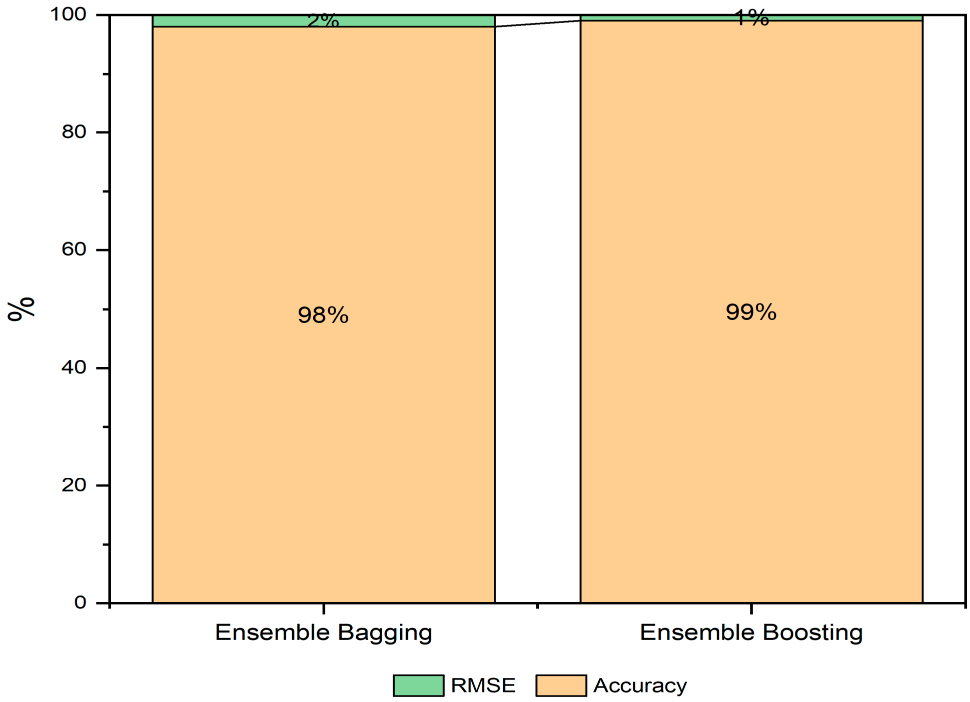
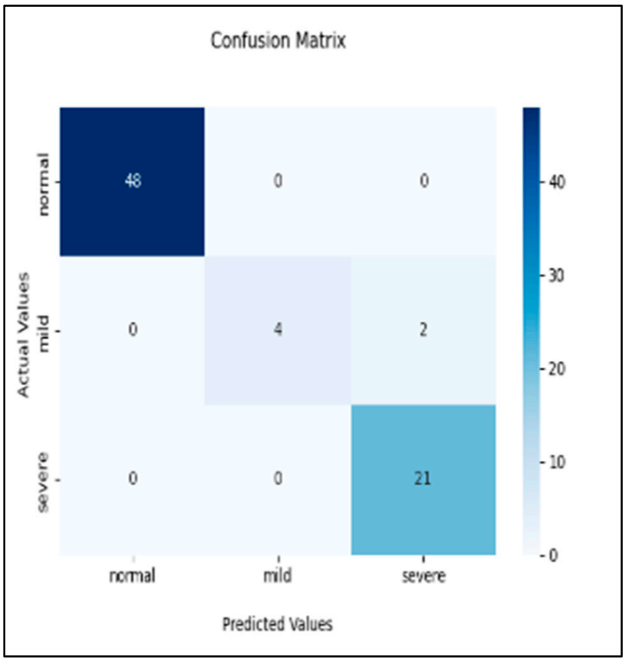
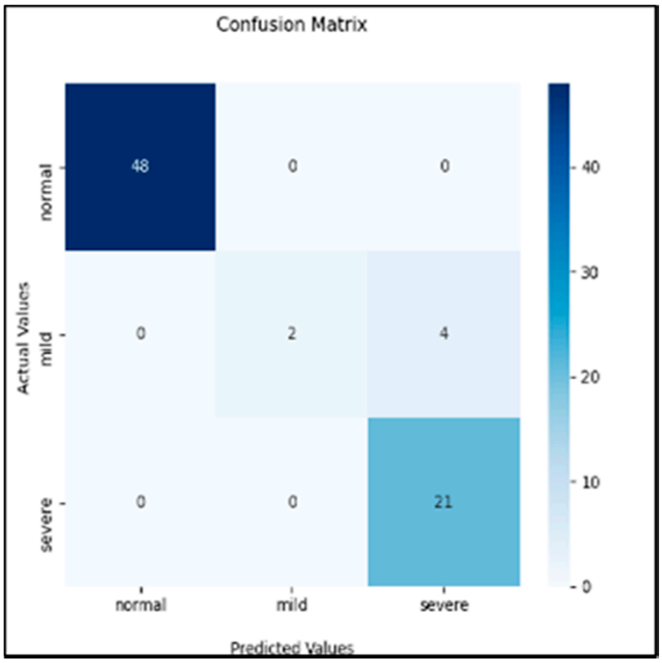


Figure 9. Regressor algorithm performance.



(**a**)



(**b**)

Figure 10. Confusion matrix using (**a**) Bagging-FLIS and (**b**) Boosting-FLIS.

Table 3 describes the evaluation time required for the bagging and boosting algorithms for the training and testing phase and is shown in Figure 11. It is observed that the boosting-FLIS model is efficient, with minimal computation time for the training and testing phase. The classification report parameters are described in Tables 4 and 5 and graphically represented in Figures 12 and 13. The precision, recall, and f-score parameters were evaluated for three output categories: normal, mild, and severe. For normal output categories, all the performance measures were performed with 100% for both algorithms.

Overall confusion matrix parameters were evaluated for f-score, sensitivity, and specificity, as shown in Figures 14 and 15. Results Tables 6 and 7 show that boosting algorithms were efficient compared to bagging-FLIS. The sensitivity and specificity performance for both algorithms were better for normal and severe output class categories with zero *FPR* and *FNR*.

Table 3. Evaluation Time.

Phase	Bagging-FLIS (s)	Boosting-FLIS (s)
Training	5.91	3.11
Testing	3.52	2.89

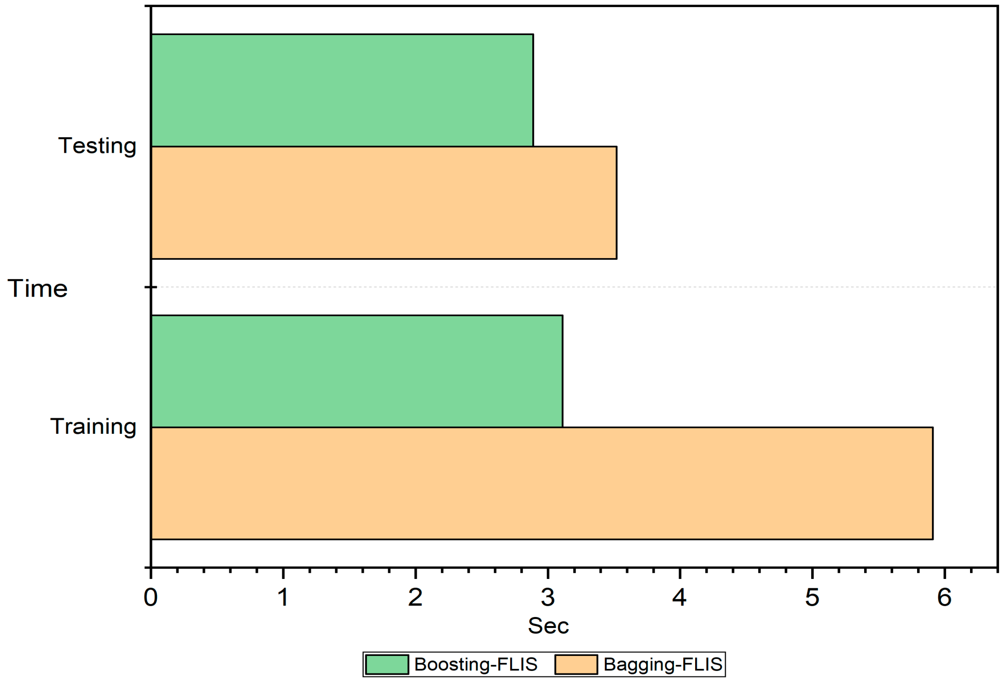


Figure 11. Evaluation time performance.

Table 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

Table 5. Classification Report for Boosting-FLIS.

Classes	Precision	Recall	F-Score
Normal	1.00	1.00	1.00
Mild	1.00	0.67	0.85
Severe	0.94	1.00	0.97

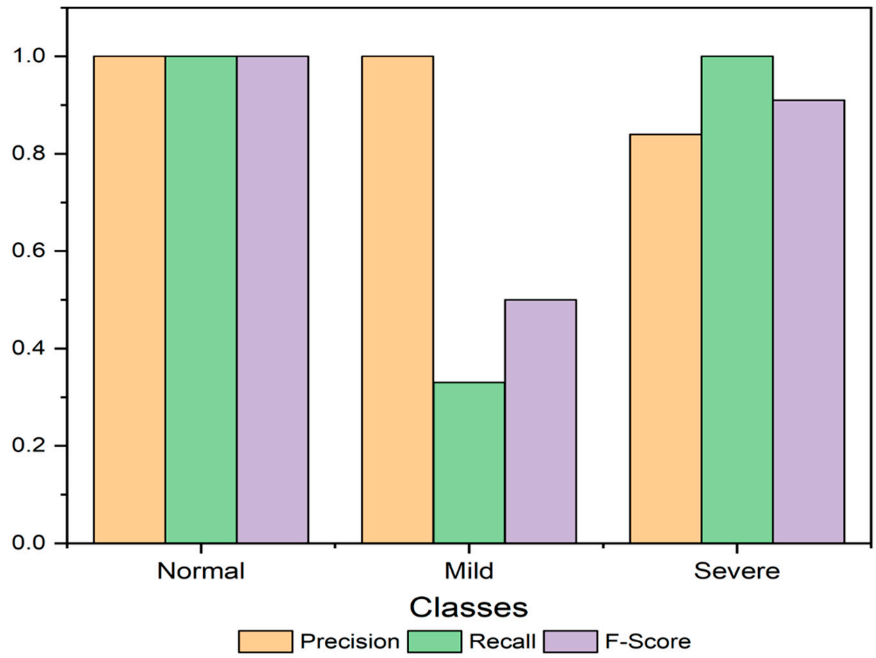


Figure 12. Performance of classification report for bagging-FLIS.

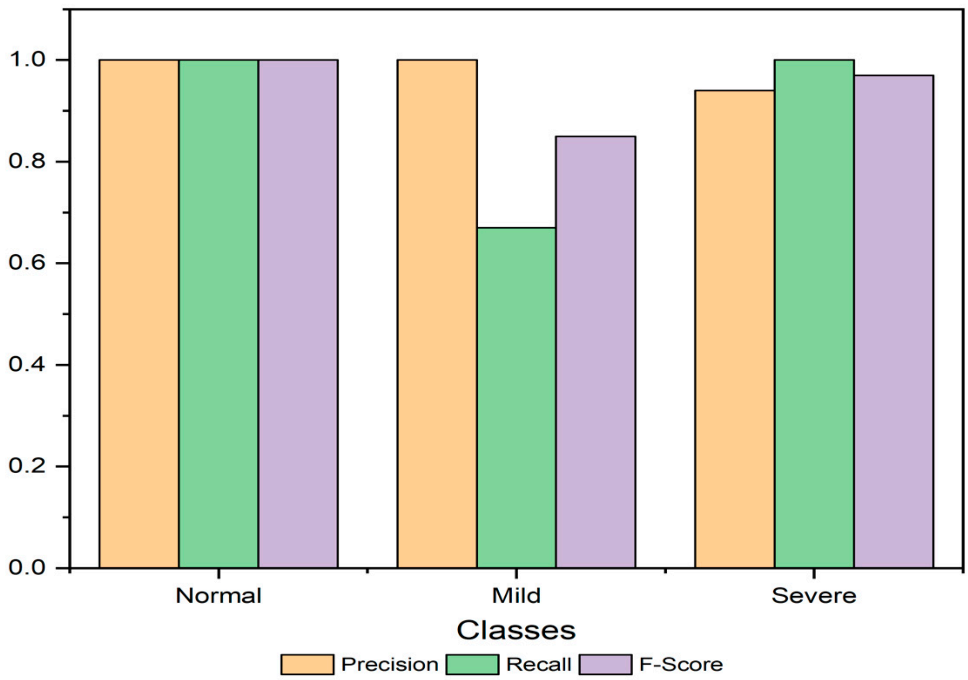


Figure 13. Performance of classification report for boosting-FLIS.

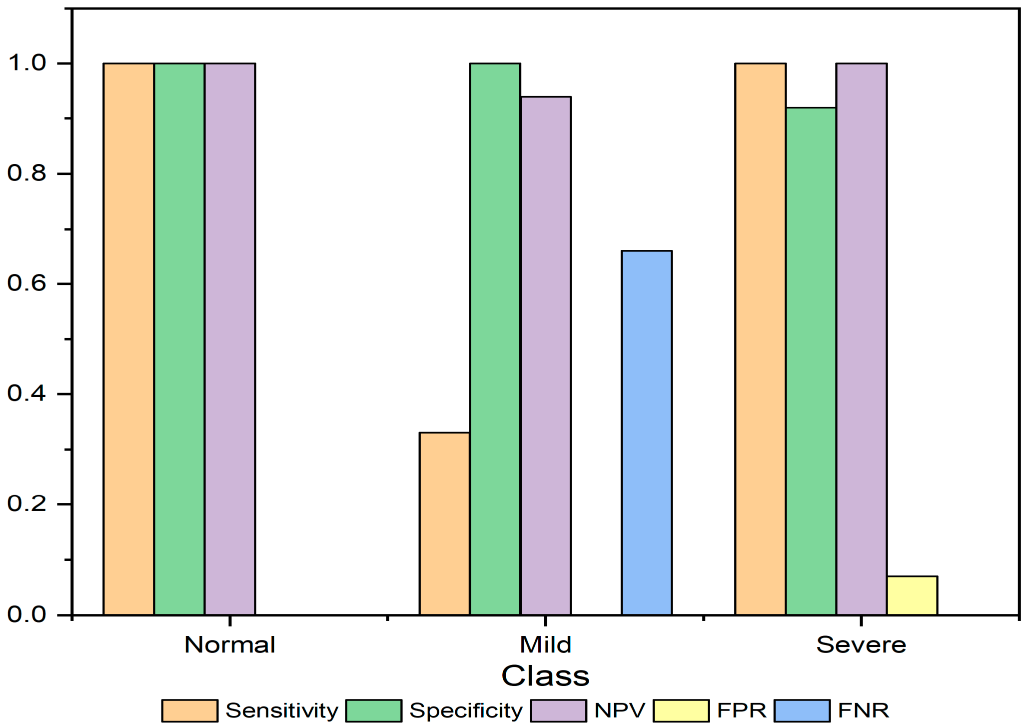


Figure 14. Evaluation parameters for bagging-FLIS.

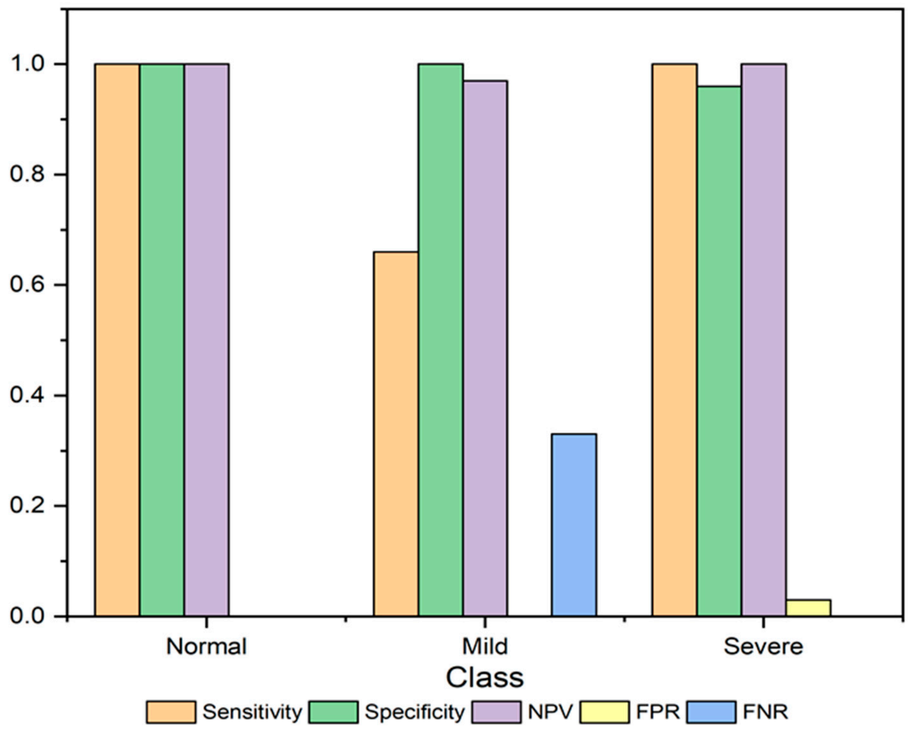


Figure 15. Evaluation parameters for boosting-FLIS.

Table 6. Confusion Matrix 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

Table 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

Figures 16 and 17 represent the ROC characteristics for bagging-FLIS and boosting-FLIS. The receiver operating characteristics, a ROC curve plot between TPR vs. *FPR*, shown in the figures, indicate the performance of a proposed model. In addition, it can be seen that the boosting-FLIS model has a high area under the curve (AUC).

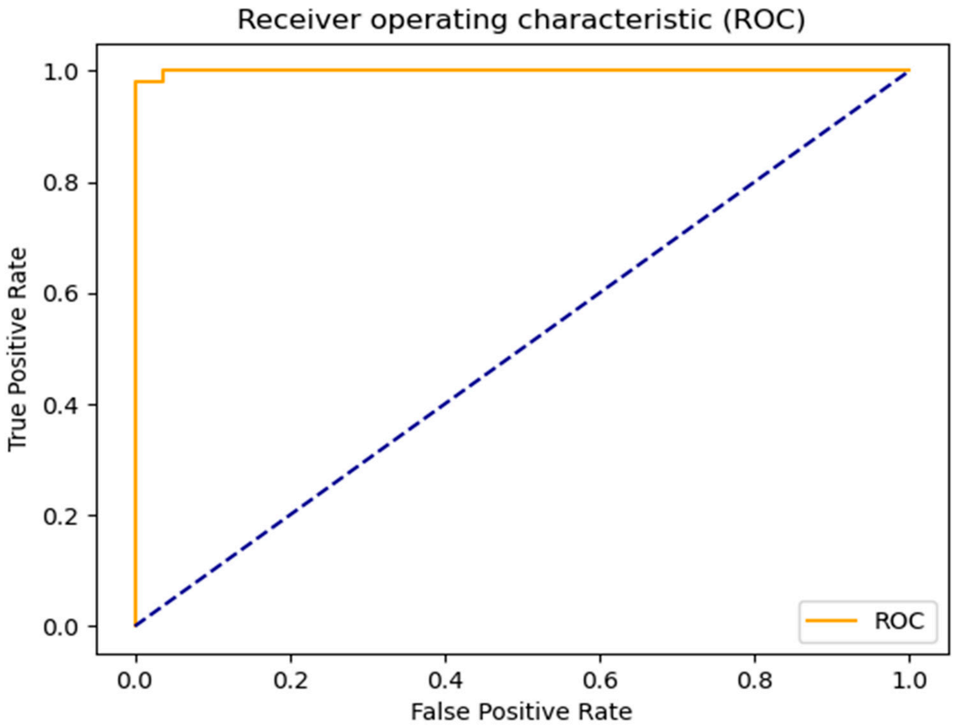


Figure 16. ROC for bagging-FLIS.

Table 8 shows a comparative analysis with the respective existing models used by various researchers. It is observed that the proposed system is able to outperform several performance measures compared to existing work. The proposed system benefited from a fuzzy logic approach with ensemble machine learning for decision-making that is simple to use and install. Furthermore, the proposed method is innovative, relying on sensor data and effective classification. Figure 18 depicts the proposed system performance parameters in comparison with the existing model, and it is observed that the accuracy of the proposed model with boosting regression approach is efficient.

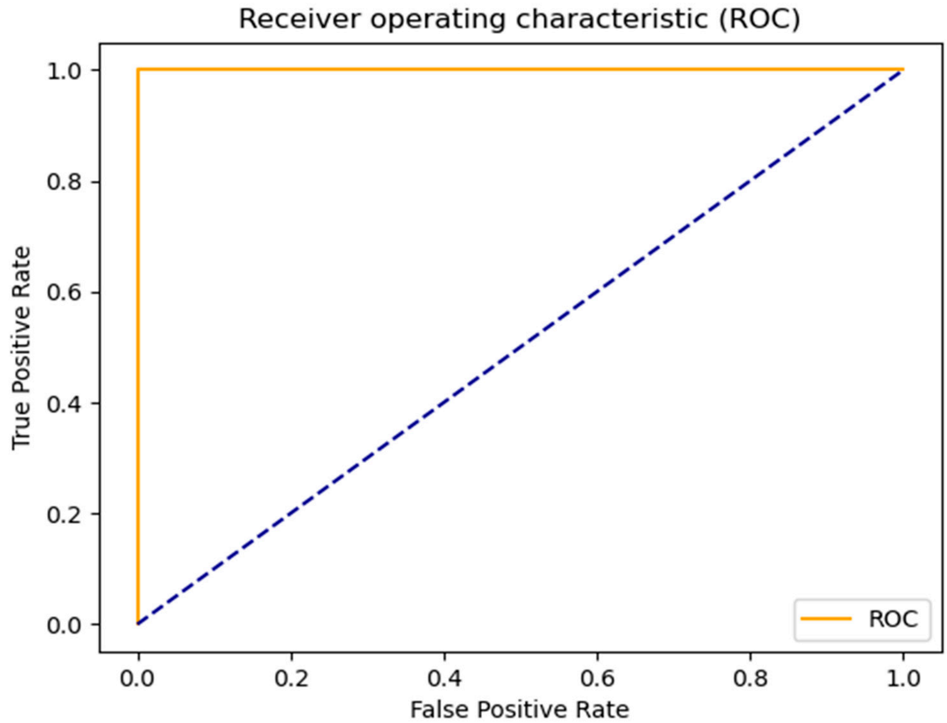


Figure 17. ROC for boosting-FLIS.

Table 8. Comparative Performance Analysis.

Ref	Accuracy	Sensitivity	Specificity	Precision	Error Rate	F Score
[8]	91.8	-	96.5	-	-	-
[9]	95.1	98.1	-	-	-	96.6
[12]	-	-	-	-	20	76
[15]	92	-	-	-	-	-
[18]	95.5	-	-	-	-	-
[25]	96.18	98.36	96.75	96.11	-	98.16
[28]	89.35	89.22	-	-	-	-
[30]	80	-	-	83	-	78
[32]	83.89	100	77.8	-	-	-
[39]	86.11	89.3	90.89	-	-	-
Boosting (AdaBoost)	97	90	98.66	97	1	94

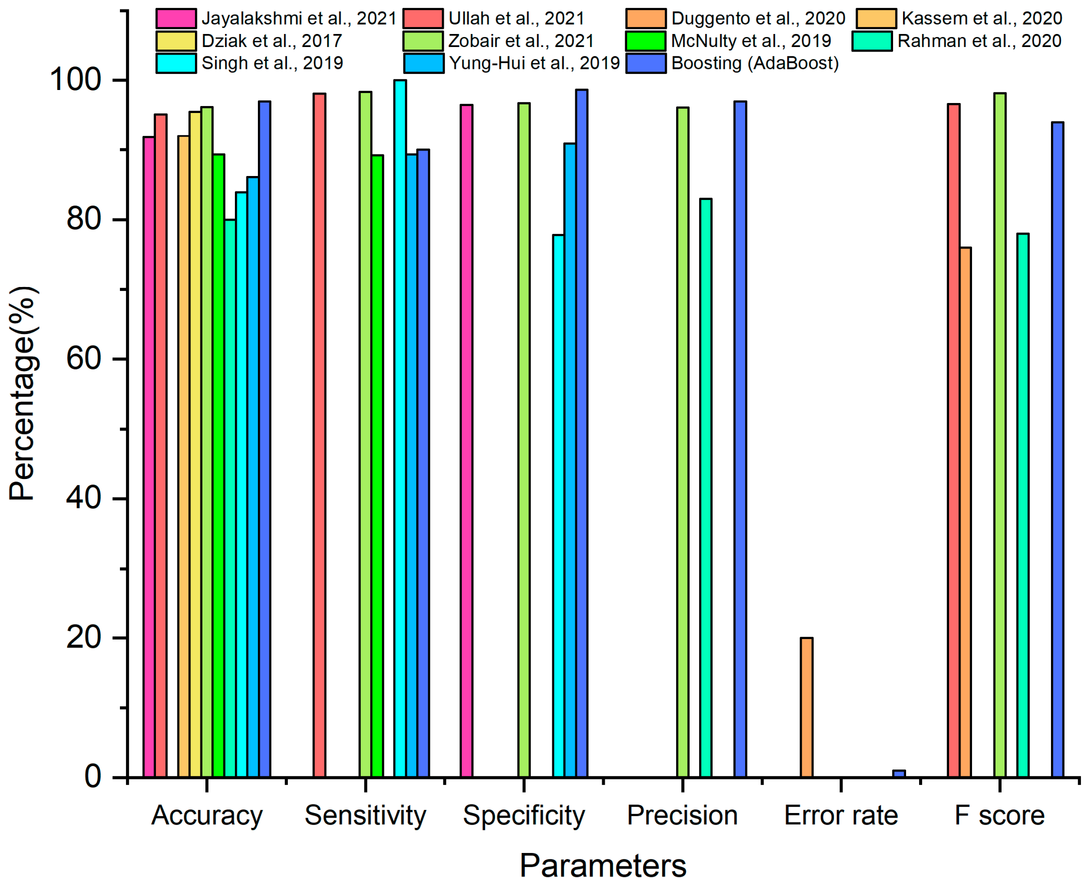


Figure 18. Comparative analysis of performance parameters with the existing methods, [8,9,12,15,18,25,28,30,32,39].

5. Conclusions

The proposed system makes intelligent patient care, monitoring, and management decisions using ensemble machine learning and fuzzy logic to determine the possible conditions of and cures for epilepsy patients. The proposed system used two ensemble machine learning-based classifiers with the fuzzy logic system to distinguish between mild and severe epilepsy and normal behaviour. The accuracy of the proposed hybrid ensemble boosting machine learning with fuzzy logic inference system approaches is 97% and was found to be efficient compared to the state-of-the-art methods. The proposed system aims to improve the system's effectiveness in terms of cost, time, and resource utilization. The proposed technique has been broad but can be adapted to more essential scenarios, including operating rooms, intensive care units, newborns, and more complicated patients. The findings also show that a machine learning–fuzzy logic system is an excellent solution for intelligent decision-making systems due to its low device and software component count. The system can be further enhanced with classification of more health parameters with the precise acquisition of parameter readings.

Author Contributions: Funding acquisition, K.O.; Supervision, M.S.; Writing—original draft, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Kingsley Ogudo and The APC was funded by University of Johannesburg.

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Patient consent was waived due to a practical problem.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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