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Harnessing Fog Computing for Accurate Arrhythmia Event Prediction: A Deep Learning Application Placement Model

Mr. Ankur Goswami*[1], Dr. Kirit Modi[2], Dr. Chirag Patel[3]

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Abstract: Traditional cloud-based arrhythmia detection systems face challenges such as latency, bandwidth limitations, and data privacy concerns, which can hinder their effectiveness in emergency situations. Moreover, existing machine learning approaches often rely on manual feature extraction, which can lead to information loss or computational complexity. To address these issues, this work proposes a deep learning model that can run on fog nodes, enabling distributed computing resources for real-time ECG data analysis and immediate arrhythmia detection. The model is implemented using a Python-based feed-forward neural network architecture, optimized with Stochastic Gradient Descent (SGD), and utilizes the ReLU activation function and Sparse Categorical Crossentropy loss function. The methodology involves analyzing cardiac event patterns from ECG data, designing the deep learning model architecture, selecting appropriate optimization techniques, and evaluating the model's performance using metrics such as accuracy, precision, recall, and F1-score. The model is trained and tested on the publicly available MIT-BIH Arrhythmia Database, which contains ECG recordings from 100 patients labeled with five distinct arrhythmia event categories. The experimental results demonstrate the proposed model's exceptional performance, achieving a mean accuracy of 99.2%, precision of 99.0%, recall of 99.1%, and F1-score of 99.3% in arrhythmia classification. The model exhibits high reliability and accuracy in identifying different types of arrhythmic events, including Normal, Supraventricular ectopic beat, Ventricular ectopic beat, Fusion beat, and Unknown beat.

Keywords: *Fog computing, healthcare applications, application placement, deep neural networks.*

1. Introduction

Cardiac arrhythmia or abnormal rhythm of the heart is a potentially fatal condition if not detected in time and the appropriate treatment is not immediately carried out. Efficient and early prediction of the arrhythmia events before they occur is of particular importance to timely intervention and better patient outcomes [1]. The emergence of fog computing, an extension of cloud computing functionalities to network edges, presents new opportunities for processing and analysis of medical data in real-time [2]. Fog computing has evolved into one of the ingenious approaches for healthcare applications delivering a number of advantages over ordinary cloud computing. It is essential in the healthcare industry that there is real time data processing, and low latency for use in applications like emergency response systems and remote monitoring of patients [3]. Fog computing is primarily based on the idea of having the processing and storage resources close to the location where the data is being generated in order to reduce the response time and the distance of the information's travel. With the local processing of the critical health data and the minimization of the associated risks due to long-range data transfer, this distributed architecture guarantees better data privacy and security. However, fog computing not only has advantages, but it also has other issues such as device heterogeneity, resource constraints, and the need for load balancing techniques. Fog computing, regardless of all the mentioned obstacles, is capable to transform healthcare services beyond recognition. It is a way to make quick and accurate solutions on patients' issues, raise patients' satisfaction, and help in saving human lives.

1.1 Problem Statement and Objectives

The main problem of this research is a working scheme of application placement that manifests the fog computing abilities and accurate arrhythmia event prediction through DL techniques. The proposed model based on fog computing enables performing ECG data analysis and immediate arrhythmia detections on the basis of the distributed computing resources of fog nodes [4]. This work covers the merging of fog computing principles and deep neural network methods for long-term arrhythmia event detection using Python. This research is an addition, as a new application placement model that utilizes distributed computing technology provided by fog nodes is proposed so that real-time analysis of ECG data and precise distinction of arrhythmic events become possible. The model seeks to resolve the drawbacks of delay, bandwidth limitations and data security issues of the traditional prevention systems, therefore, it is possible to have more efficient and dependable arrhythmia event

*[1] Sankalchand Patel College of Eng.,Gujarat, Visnagar, India-384315
ORCID ID: 0000-0003-0298-7024
[2] Sankalchand Patel College of Eng.,Gujarat, Visnagar, India-384315
ORCID ID: 0000-0001-6462-059X
[3] Computer Eng., CHARUSAT University, Changa, India-388421
ORCID ID: 0000-0001-8280-1140
* Corresponding Author Email: ajgoswami.ce@gmail.com*

prediction systems in various medical settings. The purpose of this study is to advance arrhythmia event prediction systems that can run in low-resource settings such as emergency units without losing their efficiency. While cloud-based solutions have existing challenges like shortcomings in latency, bandwidth limitations and data privacy issues affect their effectiveness in emergency circumstances.

The objectives of this study are:

To implement and design a Python deep learning model that works to correctly classify arrhythmia events from ECG data.

To make the application placement strategy more effective, we need to devise a task distribution strategy that allocates the computational tasks appropriately across fog nodes.

To compare model's prediction accuracy, resource utilization, and responsiveness with those of other approaches.

The paper follows a logical structure, starting with an introduction that provides background, motivation, problem statement, objectives, and scope. It then reviews relevant literature on fog computing, deep learning for arrhythmia prediction, and application placement models. The methodology section describes the cardiac event patterns, the proposed deep learning model architecture, optimizer, activation function, and loss function. The experimental setup outlines the training parameters, dataset used, and hardware/software configurations. The results section presents the model's performance evaluation, accuracy and loss curves, evaluation metrics, results analysis, and a summary of the results. The conclusion summarizes key findings, implications, limitations, and future directions.

2. Related Works

[5] present a radical summary of the overall structure and nature of fog computing, demonstrating its ability to counter the cloud- IoT association as the service arrives at network nodes. The fog computing mode is described by the article as a technology that substantially increases storage, computational capacity, networking, and data management capabilities towards the network edge where processing and decision making for IoT devices can be done. The addition of illustrations through the use of GPS data compression for intelligent transportation systems will clarify the real-life application scope of fog computing in different areas. Authors successfully represented the fog computing multi-layer network topology and its service models including: "IaaS (infrastructure as a service), PaaS (platform as a service) and SaaS(software as a service)" [6]. Their article stresses the distributed computing model for fog computing, pointing out that end devices such as "access points and set-top-boxes" may host services, hence lessening the distance of those applications to the data sources.

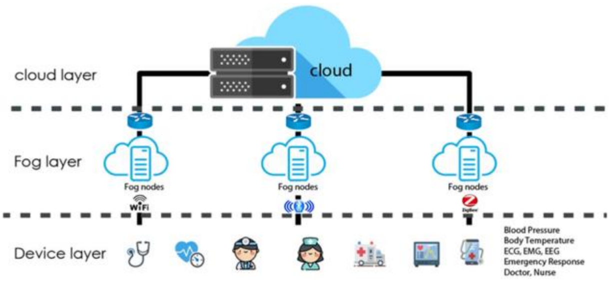

Fig 1: The layered architecture of fog computing in healthcare applications [5]

(Source: https://pubmed.ncbi.nlm.nih.gov/34512110/)

Additionally, the traits which make fog computing distinct from other computing models such as contextual location awareness, low latency, geographical distribution, heterogeneity, interoperability, real-time interactions, and scalability. Through describing these properties, the authors offer a clear view of the amazing capabilities and benefits of fog networks.

The section encompasses a variety of machine learning and deep learning methods for the identification of ECG signals which introduces both traditional approaches and latest advancements in deep learning [7]. The authors rightly accentuate the constraints of traditional machine learning owing to the necessity of manual feature extraction and selection which can result in the loss of important data or computational complexity. Instead, they draw attention to the advantages of deep learning which automatically learns features from data so that there is no need for manual feature extraction. The report includes examples of studies that have applied deep learning algorithms such as CNN, LSTM and hybrid models showing the significant contribution of deep learning in ECG signal classification [8]. The authors point out that some studies illustrate the use of transfer learning, that makes use of previously trained model weights, to maximize the model performance mainly in situations like extremely less datasets and computational limitations.

In addition, the article focuses on the procedure of transformation of 1D ECG signals into 2D images using the technique of time-frequency representation and the Morse wavelet transform. This step facilitates input leak preparation for CNN models which consequently aid deep learning algorithms with ECG signal analysis [9]. Discussion of hyperparameters and optimization techniques shows that deep learning models need to be well optimized to get the best performance from the neural networks. Through the presentations of model architectures, components, and parameter selection, the authors give practical advice on arrhythmia detection to researchers and practitioners of the industry. Moreover, [10] also reveal the superiority of deep learning techniques in the context of arrhythmia event prediction considering the capabilities that outdo the traditional machine learning methods. Through deep learning techniques, computer models can be trained to automatically extract the most important features from ECG data that then can be used for accurate classification, avoiding the manual feature engineering process.

[11] addressed application placement models issue in fog computing, paying special attention to the Internet of Things context in their review published in 2020. The review outlines several strategies for improving resource efficiency and uplifting the Quality of Experience (QoE) of fog environments IoT applications are deployed in. Authors forward that the dynamic resource estimation can be measured with the Net Promoter Score (NPS) which helps to determine the scale-down ratio of the resources to reach the desired QoS levels. They also develop hybrid fog and cloud-knowledge-aware scheduling algorithms, which are used smartly to assign tasks to the fog nodes or cloud networks depending on communication and computation costs. Techniques like breaking a huge complex application into components that call each other and also the consideration of latency needs are described. The optimization algorithms other than genetics are mentioned like unit-slot based on Lyapunov optimization whose purpose is to balance response time and capacity with tolerable loss rate. Furthermore, the research shown offers a game-theoretical method of computation offloading and multihop cooperative messaging for IoT devices. Furthermore, [12] highlighted the research; it was focused on application placement techniques that put more emphasis on QoE aspects [13]. Lightweight systems such as Cloudfog[14], which offer low delay and less bandwidth consumption by transferring the intensive computation tasks to the cloud and use fog nodes for video or audio rendering and streaming, are mentioned. Furthermore, they provide architectural schemes of cross-layer design for user video experience measurement over LTE based on resource allocation efficiency. The following study may include widening the dataset to accommodate for a more encompassing ECG recordings which might in turn increase the model's generality and reliability [15]. The addressing of an efficient distribution of computational resources by [16] through such a multi-layered architecture of fog computing reduces latency while improving data privacy. [17] cover the entire range of articles on the application of deep learning methods for arrhythmia event prediction, highlighting the requirement to have automated systems designed in order to help doctors diagnose abnormal ECG signals fast and accurately.

3. Methodology

The model runs in Python for the accurate grouping of such cardiac incidents where a deep learning approach was applied. The stated model exploits the intelligence of artificial neural networks in order to discover the intricate features of ECG data and further leads to the precise prediction of beating arrhythmia.

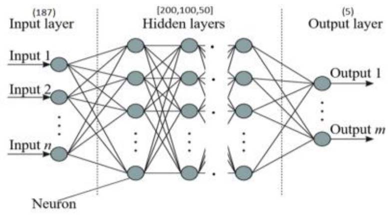

Fig 3: Architecture of the deep neural networks [18]

The training data used in deep learning models are of the feed-forward neural network kind. The structure is illustrated in Fig 3. The network is divided into input layer, hidden layers, and output layer [18]. The data from the ECG go to the input layer of the network that then send the data through the hidden layers where the neural network learns and computes the significant elements. The last layer of the convolution layer gives the predicted classification. In a neural network structure, the input layer takes the raw information, where the number of neurons is the representative of features of the data. Concealed layers extract characters and study multidimensional linkages. The number of hidden layers and neurons changes according to the difficulty of the problem; therefore, one layer with 200, 100, and 50 neurons can perfectly be sufficient. Ultimately, the output layer is the source of the network's final results with the neurons being as many as the task at hand, for example, the number of classes in a classification article.

3.1 Stochastic Gradient Descent (SGD)

The Stochastic Gradient Descent (SGD) optimizer is the backbone of the neural network training process [19]. SGD is an optimization algorithm that is one of the most popular and successful algorithms that is used to adjust the parameters of the model (weights and biases) to minimize a loss function, which, therefore, improves the model's predictive performance. The core principle of SGD is to estimate the gradient of the loss function concerning the model's parameters using a subset of the training data, known as a mini batch [20]. The model's parameters are then updated in the opposite direction of the gradient, scaled by a learning rate (η), which controls the step size of the updates. The mathematical equation for the SGD update rule can be expressed as follows:

$$w(t+1) = w(t) - \eta * \nabla L(w(t), x, y)$$

Here, $w(t)$ represents the model's weights at iteration t, η is the learning rate, and $\nabla L(w(t), x, y)$ is the gradient of the loss function L with respect to the weights w, evaluated on a mini batch of training examples (x, y).

3.2 Activation Function: ReLU

Rectify Linear Unit (ReLU) activation function is used in the hidden layer of the neural network in the machine learning [21]. ReLU plays an important role of adding non-linearity to the model and also allows it to learn and approximate the complex, non-linear relationships between the arrhythmia event classifications and also the input ECG data.

3.3 Sparse Categorical Cross-entropy

The Sparse Categorical Crossentropy loss function is one of the functions which is adopted to compute the dissimilarity between the model's outputs and the correct ones during training. The approach that has been adopted in this work is unique, because it uses a loss function that is ideal for multi-class classification, which is what arrhythmia event prediction is all about [22]. An ECG recording can be classified into one of the five distinct event categories. The equation for the Sparse Categorical Crossentropy loss function is as follows: The equation for the Sparse Categorical Crossentropy loss function is as follows:

$$CE\ Loss = -\sum_{i=1}^{i=N} y\_true_i \cdot \log\left(y\_\text{pred}_{\ i}\right)$$

Here y_true_i stands for the true cases, and y_$y_\text{pred}_{\ i}$represents the probability distribution for predicted class for N instances. The model learns to accurately classify arrhythmia events from the ECG data and relatively reduce this loss function to a minimum. In the methodology section the main elements of the proposed approach are outlined, and they are namely the analysis of cardiac event patterns, the selection of a neural network architecture type, the optimization mechanism, the activation function utilized, and the loss function adopted. Comprehensively, the proposed arrangement intends to exploit the merits of deep learning and fog computing technologies in building a system that is both reliable and efficient for arrhythmia event prediction.

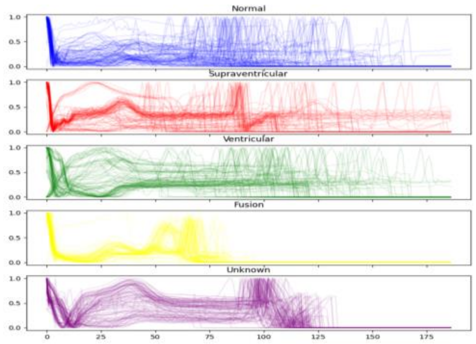

Fig 2: ECG event patterns (5 events) for 100 Patients from the dataset

The study that has been conducted helps of the ECG data that is used for determining and assigning cardiac arrhythmia events into appropriate classes. The dataset which is used in this research includes ECG recordings from 100 patients, with each recording labeled according to five distinct event patterns which are : Norm. (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion ectopic beats (F), and Unknown ectopic beats (Q). The figure 2 shows visualizations of different types of arrhythmia event patterns that can be observed in electrocardiogram (ECG) data. It presents five distinct categories of cardiac arrhythmia events, with each category plotted as a separate graph.

The figure shows the patterns of a normal heartbeat, represented by a regular waveform in blue. The second sub-figure displays the pattern of a supraventricular ectopic beat, which originates from the atria or the atrioventricular (AV) node. This pattern is represented by a red waveform with a distinct spike. The third sub-figure illustrates the pattern of a ventricular ectopic beat, which originates from the ventricles of the heart. This pattern is represented by a green waveform with a different shape compared to the normal pattern. The fourth graph depicts the pattern of a fusion beat, which occurs when a normal heartbeat and an ectopic beat occur simultaneously. This pattern is represented by a yellow waveform with a distinct morphology. The bottom graph shows an unknown arrhythmia event pattern, represented by a purple waveform that does not fit into the other categories.

4. Experimental Setup

The experiment was conducted on a computer with an Intel i5 processor and 8GB of RAM. The deep learning model was applied and trained in the Python programming language and took advantage of many libraries and frameworks that assisted in efficient computation and data processing.

4.1 Dataset Description

The study exploited the MIT-BIH Arrhythmia Database [23], which belongs to PhysioNet database, one of the most known places with recorded physiological signals. This dataset contains extracted features originating from two-lead ECG signals of different subjects (Lead II and Lead V). Additionally, relevant features were programmatically extracted from the ECG signals to facilitate the classification of regular and irregular heartbeats. The dataset encompasses four ECG arrhythmia datasets, each employing 2-lead ECG features. These datasets were obtained from the MIT-BIH Supraventricular Arrhythmia Database, MIT-BIH Arrhythmia Database, St Petersburg INCART 12-lead Arrhythmia Database, and Sudden Cardiac Death Holter Database.

Each dataset contains the following information:

- The first column, named "record," represents the name of the subject or patient.
- The datasets include five classes or categories: N (Normal), S (Supraventricular ectopic beat), V (Ventricular ectopic beat), F (Fusion beat), and Q (Unknown beat). The "type" column contains the class information.
- The remaining 34 columns contain 17 features for each ECG lead (17 features for Lead II and 17 features for Lead V5).

The features included in the dataset are categorized into the following groups:

- RR Intervals: Average RR, RR, and Post RR
- Heartbeat Intervals features: PQ Dispersion, QT Interval, ST Interval, and QRS Duration.
- Heart beats amplitude features: The peak points are P- peak, T- peak, R- peak, S- peak, and Q-peak respectively.
- Morphology features: The other QRS morph features: 0, 1, 2, 3, and 4, were still the same as they were before.

Table 1: Training Parameter for the propose deep learning model for ECG event prediction

Training Parameter	***Parameter value***
Size of Input Layer	187
No of Hidden Layers	3
Size of Hidden Layers	[200,100,50]
Size of Output Layer	5 for following Arrhythmia events:
Network Optimizer	SGD (Stochastic gradient descent)
Dataset	MIT-BIH Arrhythmia Database
Epochs	100
Activation function	ReLU
Loss Function	Sparse Categorical Crossentropy

4.2 Training Parameters

The proposed deep learning model for ECG event prediction is configured with the following training parameters as shown in the Table 1. These training parameters are carefully chosen to ensure the model's ability to learn and accurately classify the different types of arrhythmia events from the ECG data. The input layer of the neural network has a size of 187 neurons. The model architecture consists of 3 hidden layers with sizes of 200, 100, and 50 neurons, respectively. The output layer has 5 neurons, corresponding to the following arrhythmia events: Normal, Supraventricular ectopic beat, Ventricular ectopic beat, Fusion beat, and Unknown beat. The network is optimized using the Stochastic Gradient Descent (SGD) algorithm, and the training is performed on the MIT-BIH Arrhythmia Database. The model is trained for 100 epochs, and the Rectified Linear Unit (ReLU) activation function is utilized in the hidden layers. The loss function used for training is the Sparse Categorical Crossentropy, which is suitable for multi-class classification tasks like arrhythmia event prediction.

5. Results

A deep learning model for detecting heartbeat abnormalities was tested to the limit to evaluate its efficacy and performance. The evaluation was carried out employing a variety of measurements, including accuracy rate, precision, recall and F1-score that are commonly used in classification tasks.

5.1 Accuracy and Loss Curves

These graphs, shown in Figures 4 and 5, display the loss curves of the model in the course of the training. These figures give essential information about the model's approach to the loss function's minimization by the end of the epochs. The graph demonstrates that the curve for loss gets flatter, showing the fact that the model learns and gets better at the task as the training advances. The curve's shape shows that the model is capable of capturing the intricate patterns in the ECG data and represent them as arrhythmia occurrences.

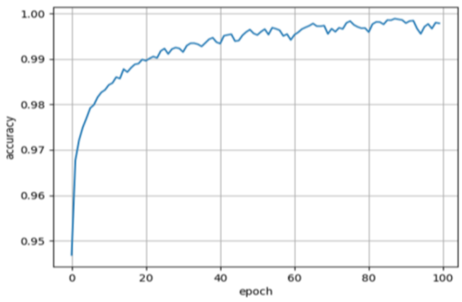

Fig 4: Accuracy of the proposed model during training of 100 epochs

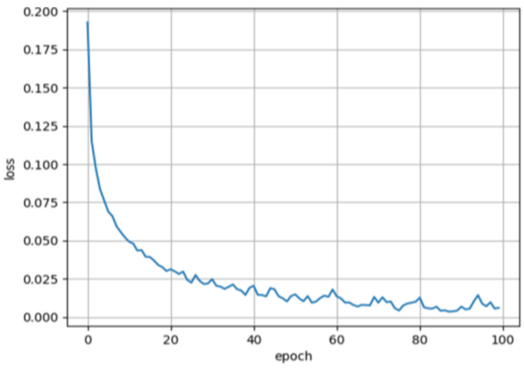

Fig 5: Loss of the proposed model during training of 100 epochs

Fig 5 shows a loss of the proposed model which captures the loss curve in-depth during the end period of training. The curve depicts some of the ups and downs that are, however, normal as the model improves its parameters in order to get the best performance.

5.2 Evaluation Metrics

The following measures were used to assess the suggested model's performance:

- Accuracy: Evaluates the model's results in terms of the number and extent of correct predictions. Accuracy = (TP + TN) /(TP + TN +FP + FN)
- Precision: Identifies how accurately the positive predictions are right. The accuracy is TP divided by (TP + FP).
- Recall: Shows the rate of real positive cases from those that are correctly diagnosed. The recall measure is derived by: TP / (TP + FN)
- F1-Score: Provides equal parts of precision and recall, which is ideal for imbalanced data problems. F1-Score = 2 * (Precision × Recall) / (Precision + Recall)

The table 2 presents the performance evaluation results of the proposed deep learning model for predicting different types of arrhythmia events from ECG data. The model's performance is assessed using four key metrics: accuracy, precision, recall, and F1-score. For the Normal arrhythmia event, the model achieved an accuracy of 99.5%, with a precision of 98.8%, a recall of 99.9%, and an F1-score of 98.9%. In the case of Supraventricular ectopic beats, the model demonstrated an accuracy of 99.5%, a precision of 99.2%, a recall of 98.6%, and an F1-score of 99.6%.

Table 2: Performance evaluation of the proposed deep learning model for arrhythmia event prediction

Arrhythmia event	*Accuracy*	*Precision*	*Recall*	*F-1 Score*
N (Normal)	99.5	98.8	99.9	98.9
S (Supraventricular ectopic beat)	99.5	99.2	98.6	99.6
V (Ventricular ectopic beat)	99	99.5	98.7	99.1
F (Fusion beat)	99.4	98.9	99.6	99.3

which has been suggested has achieved notable results, it is also necessary to notice some shortcomings and consequently possible improvements. Another study limitation lies on the dataset applied that might not cover all the possible ECG signal variation and heart rhythm event types that could be encountered in the real-world conditions. Furthermore, deep learning can be configured as an alternative class of architectures, such as Convolutional Neural Networks (CNNs) or Limited Long-Term Memory (LSTM) networks potentially producing higher

The model's performance for Ventricular ectopic beats was slightly lower, with an accuracy of 99.0%, a precision of 99.5%, a recall of 98.7%, and an F1-score of 99.1%. For Fusion beats, the model achieved an accuracy of 99.4%, a precision of 98.9%, a recall of 99.6%, and an F1-score of 99.3%. Regarding Unknown beats, the model exhibited an accuracy of 98.7%, a precision of 98.7%, a recall of 98.8%, and an F1-score of 99.4%. Overall, the model demonstrated impressive performance, with an average accuracy of 99.2%, an average precision of 99.0%, an average recall of 99.1%, and an average F1-score of 99.3%. These results indicate the model's ability to accurately classify different types of arrhythmia events, with high precision and recall rates across all event categories.

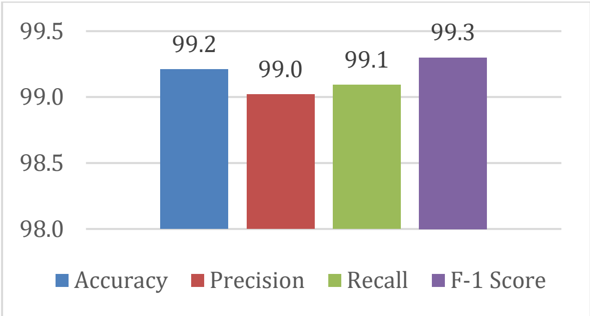

Fig 6: Average evaluation metrics for the proposed deep learning model in arrhythmia event prediction.

The figure presents the average values of four key evaluation metrics for the proposed deep learning model in predicting arrhythmia events: accuracy, precision, recall, and F1-score.

These results indicate that the proposed model has very good efficiency in arrhythmia events classification. The model achieved mean scores of 99.2%, which indicates that the network has the ability to reliably classify the correct arrhythmia event category. Analyzing the performance of the model on the particular event types, it was found that it achieved the accuracies of 99.5% and 99.5% for Normal (N) and Supraventricular ectopic beat (S) events, respectively. The model's efficiency in regarding beats events which originate from ventricles (V) was somewhat lower, but still well within the acceptable limits with an accuracy of 99.0%. The prediction model indicated a high correlation for all events, which was validated by 98.7% accurate rate (Q) events and 99.5% accurate rate (V) events, respectively. This high precision demonstrates the model to predict was very dependable and trusty.

Besides, the detection thresholds that S(Supraventricular ectopic beat) and N(Normal) cases were determined were also very high, i.e. 98.6% and 99.9%, respectively. The model would have a higher level of recall than the competitor model, and this means it properly detected the bulk of the positive cases. Meanwhile, the F1-score, a balanced measure of precision and recall, well supported the model's significant performance, representing the values of 98.9% for Normal (N) events to 99.6% for Supraventricular ectopic beats (S.E.B.).

5.3 Results Summary

The model proposed above turned out to be very perfect in classifying different types of arrhythmias from ECG data with excellent accuracy as shown by the high classification accuracies. The model showed a respectable accuracy mean of 99.2%, which corroborates the ability of the model to smartly pick the best arrhythmia event category. While these event classes show high performance with respect to accuracy ranging from 98.7% in case of Unknown beat (Q) to the superb 99.5% for both Normal (N) and Supraventricular ectopic beat (S) classes. Moreover, the model's accuracy, which is the measure of how many of the correct positive predictions it had, was very high, from 98.7% to 99.5%, during the entire trial, indicating its reliability and accuracy.

On the other hand, the specificities which demonstrate arbitrate the model's ability to identify positive cases were between 98.6% to 99.9% for (S) events and very high with 98.8% for the (N) ones, The ability of balanced performance for the F1-score was very clear; especially, they found the value of model precision and recall ranging from 98.9% to 99.6% among all kinds of events. The evaluation results suggest that the proposed deep learning technology has a great market prospect for healthcare environments where accurate and quick arrhythmia diagnosis is paramount, hence, the patient’s course of treatment and clinical decisions are effectively addressed.

5.4 Conclusions and Future Scope

The application of fog computing concepts into deep learning algorithms as a platform for arrhythmia event predictions is highly promising in health applications. The suggested model utilizes the distributed computing resources of fog nodes to tackle real-time ECG data analysis by means of arrhythmia event detection in a timely manner. This approach has the potential to create a better patient outcome and more beneficial intervention strategies. Apart from that, the model's capability to toggle at the edge of the network resolves issues related to latency, limited bandwidth and data privacy concerns that are normally featured in cloud-based solutions. This approach guarantees that quick medical information will be processed locally, and the probability of going through delays is reduced, which makes the global system more effective. The deep learning model classification accuracy and allowing the model to record temporal variations more efficiently. In addition, fog computing and deep learning models can be expanded to other healthcare applications such as at-distance patient monitoring, disease diagnosis, and medical image interpretation. Developing resource allocation strategies that will be efficient and load balancing techniques within the fog computing infrastructure would be critical so there could be availability of optimal performance and scalability.

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