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Harnessing Deep Learning for Early Detection of Cardiac Abnormalities

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Abstract: Sudden Cardiac Arrests (SCAs) are potentially lethal events that occur suddenly and without warning, causing the heart's electrical system to malfunction and impairing heart function. If not addressed promptly, these events can lead to serious consequences. Early detection and timely intervention are crucial for increasing survival rates and minimizing long-term damage. In this context, this study explores the potential of using fog computing and Deep Learning (DL) algorithms in conjunction with Internet of Things (IoT) devices to improve the understanding and prediction of SCAs. The primary goal is to create a reliable, real-time system capable of detecting potential SCA events, analyzing relevant data, and enabling prompt interventions. The study employs a multidisciplinary approach, combining fog computing for IoT devices with machine learning techniques. Fog computing is used to collect and process real-time data from wearable devices like smartwatches and health monitors at the edge, while DL algorithms, specifically a Multilayer Perceptron with ReLU as the activation function for faster convergence, are used to detect patterns and anomalies that may indicate an impending SCA. The model achieved an impressive average accuracy of 99.52%, outperforming previous models and converging more rapidly. One of the key innovations of the study is an alert system that sends notifications when an SCA is predicted. The findings indicate that combining DL, fog computing, and IoT devices significantly enhances the understanding of SCAs. The system's ability to process and analyze data in real time allows for swift, targeted interventions, potentially saving lives. Additionally, the continuous learning capabilities of the DL algorithms enable the system to improve its predictive accuracy over time, making it a valuable tool for cardiovascular health monitoring. This research demonstrates how the integration of machine learning, particularly DL, with fog computing can transform our understanding of and response to SCAs, paving the way for advancements in emergency response systems and healthcare.

Keywords: Deep Learning, Sudden Cardiac Death, Early Detection Mechanism, Artificial Intelligence for Medicine

1. Introduction

Sudden Cardiac Arrests (SCA) are a critical medical emergency requiring immediate and precise intervention for the best outcomes. They are often unpredictable and can be fatal if not treated promptly. Given their significant impact on public health, advancing our understanding of SCA and improving response mechanisms is paramount. The American Heart Association (AHA) reports over 356,000 Out-of-Hospital Cardiac Arrests (OHCA) occur annually in the U.S., with nearly 90% being fatal. There is a need for better surveillance systems to monitor cardiac arrest occurrences, as current estimates rely on registries and clinical trials. The annual incidence of EMS-assessed OHCA is 356,461 as seen in Figure 1. [1]

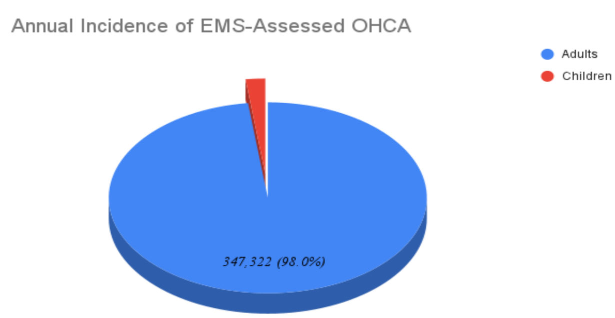

Figure 1. Annual Incidence of EMS Assessed OHCA.

This need for better monitoring systems gives rise to

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the convergence of cutting-edge technologies, such as fog computing and Machine Learning (ML) and Deep Learning (DL) with healthcare; offering new possibilities for addressing the complexities of SCA. Fog computing, which extends cloud computing to the edge of the network, and DL, which enables systems to learn from data, are particularly promising in this regard. The American Heart Association[2] highlights the increasing use of remote monitoring systems powered by IoT in detecting and managing cardiac abnormalities, including sudden cardiac arrest. IoT technology enables continuous monitoring of cardiovascular metrics, significantly aiding in early detection and personalized intervention strategies. A report from MarketsandMarkets[3] indicates that the global fog computing market in healthcare is expected to grow from USD 1.7 billion in 2022 to USD 5.4 billion by 2027, at a CAGR of 25.3% during the forecast period. All of these factors bolster the motivation of the authors to conduct this study.

This research explores the synergistic potential of fog computing and DL within the framework of the Internet of Things (IoT) to provide a comprehensive and innovative approach to understanding, predicting, and effectively managing sudden cardiac arrests. By leveraging data analytics at the edge of the network, this work aims to revolutionize real-time comprehension and response to SCA events.The integration of fog computing and DL in IoT devices holds the promise of enhancing cardiovascular health monitoring and emergency medical care. It has the potential to enable early detection of SCA risks, timely interventions, and personalized treatment strategies, ultimately leading to improved patient outcomes and a reduction in SCA-related mortality rates.

2. Related Works

The research presented in [4] evaluates the performance of various deep learning architectures in the classification of ECG arrhythmias. The study compares the effectiveness of different models, including LSTM and CNN-based approaches. In [5], the study investigates the potential of edge computing for real-time ECG data processing and analysis. The research highlights the advantages of edge-based solutions in reducing latency and improving the efficiency of ECG monitoring systems. The study in [6] explores the use of transfer learning techniques for ECG signal classification across different populations. The research demonstrates the effectiveness of transfer learning in adapting models to diverse patient demographics. According to [7], the integration of ECG monitoring with wearable technology and mobile health applications is reviewed. The study examines the impact of such integrations on patient engagement and adherence to monitoring protocols. The research presented in [8] investigates the application of hybrid machine learning models for ECG signal analysis. The study focuses on combining different algorithms to enhance classification accuracy and robustness. In [9], the study explores the use of ensemble learning techniques for ECG arrhythmia detection. The research highlights the benefits of combining multiple classifiers to improve diagnostic performance. In [10] the purpose of the study is to evaluate and compare various transfer learning techniques for ECG classification in the context of ECG arrhythmia detection. An ECG dataset from Kaggle is multi-classified using the proposed model, CAA-TL, which is enhanced with real-time and other datasets (healthy and unhealthy).The study in [11] evaluates the impact of noise reduction techniques on ECG signal quality and classification accuracy. The research focuses on various methods for preprocessing ECG data to enhance diagnostic reliability. In [12], the research explores the use of attention mechanisms in deep learning models for ECG signal classification. The study demonstrates how attention mechanisms can improve the interpretability and accuracy of ECG analysis. According to [13], the integration of ECG data with other health metrics, such as physical activity and sleep patterns, is reviewed. The study highlights the potential for comprehensive health monitoring and personalized treatment strategies. In [14] the study's objectives are to examine and assess unsupervised ECG clustering methods, most of which have been created in the previous ten years. Recent advances in machine learning and deep learning algorithms, along with their useful applications, are the main focus. [15] The research noted that while various attempts have been made to quantify diagnostic distortion brought about by low-dimensional ECG representation techniques, no widely recognized quantitative measure has been developed specifically for this purpose. The purpose of the suggested framework was to address the need for an effective and dependable way to evaluate diagnostic distortion brought on by ECG processing methods.[16] The study's findings highlight the distinctions between the two AI-ECG techniques, ML and DL. With a focus on particular ECG variables for focused tasks such wide QRS complex (The QRS complex is the waveform in an ECG that reflects the electrical activity as the heart's ventricles prepare to pump blood by contracting.) tachycardia discrimination, the machine learning approach makes use of expert domain knowledge. On the other hand, for more general tasks like a thorough 12-lead ECG interpretation, the DL technique depends on a more extensive and independent recognition of several ECG parameters. The study highlights how crucial it is for researchers working on AI-ECG solutions to comprehend these distinctions. In [17], the study investigates the effectiveness of various feature extraction techniques for ECG signal processing and classification using machine learning algorithms. The research focuses on the impact of feature selection on classification accuracy and the potential for integrating advanced algorithms to enhance diagnostic capabilities. According to [18], the implementation of wearable ECG monitoring systems has significantly advanced the ability to detect arrhythmias in real-time. The study reviews various wearable technologies and their performance in continuous heart rate monitoring and arrhythmia detection. The research presented in [19] explores the use of convolutional neural networks (CNNs) for ECG signal classification. The study highlights the improvements in diagnostic accuracy achieved by CNNs compared to traditional machine learning methods. In [20], the study examines the integration of ECG data with other physiological signals, such as blood pressure and temperature, for comprehensive cardiovascular monitoring. The research emphasizes the potential benefits of multi-modal data fusion in improving diagnostic accuracy. The study in [21] reviews the application of reinforcement learning techniques for real-time ECG monitoring and anomaly detection. The research focuses on the adaptability of reinforcement learning algorithms to dynamic cardiac conditions. According to [22], the use of Generative Adversarial Networks (GANs) for augmenting ECG datasets is explored. The study demonstrates how GANs can generate synthetic ECG signals to enhance training datasets and improve the robustness of classification models.In [23] during ECG patch monitoring, the PPG-based algorithm showed a high positive predictive value for concurrent AF detection. Numerous participants were successfully enrolled in the study, yielding a diverse dataset for analysis. Fitbits in particular are wearable technology that could be useful in identifying people who have undiagnosed AF.According to [24], the development of real-time ECG monitoring systems using IoT technologies is reviewed. The study emphasizes the potential of IoT for enabling continuous heart health monitoring and timely intervention. In [25] with training and application on 3D VCG, the DL architecture showed improved precision with high F1-scores of 99.80% and 99.64% in leave-one-out cross-validation and cross-database validation protocols, respectively.[26] The study's findings highlight the clinical significance of minute variations in QRS when evaluating diastolic dysfunction, decreased EF, the onset of HF, and the responsiveness of therapy. The study acknowledges that precise physical measurements are necessary to detect these minute variations, but it also proposes that using artificial intelligence (AI) to analyze ECG data may result in a faster and more thorough evaluation, particularly when working with big populations. [27] Several research gaps in the field of AI-based electrocardiography are identified by the review. First of all, it points out that the majority of research are proof-of-concept investigations, and it's frequently unclear what level of private data was used in these studies. This implies that more extensive and standardized datasets are required, and the authors stress the significance of clinical validation in various contexts and collectives. Artificial intelligence (AI) solutions are often perceived as being opaque, which highlights the necessity for AI algorithms to be transparent and comprehensible. [28] The article's observations highlight how AI is revolutionizing ECG analysis. The conversation is on the enthusiasm that machine learning and computer techniques have brought about, which has resulted in the revival of the ECG, one of the most important diagnostic instruments. [29] The findings demonstrate that, despite its lengthy history, electrocardiography is still relevant today. The growing interest in ECG is ascribed to advances in artificial intelligence (AI), namely in the areas of machine learning and deep learning, which are predicted to open up new avenues for the assessment and interpretation of ECG data. The reference to overcoming shortcomings in traditional computer-assisted ECG examination points to a positive assessment of AI's potential to solve problems in this field. [30] The study takes a broad approach, integrating knowledge from the supervised AI algorithms' mathematical foundation with an emphasis on their use in Electro-Cardio-Gram (ECG) analysis (An ECG is a test that records the heart's electrical activity to assess its rhythm and function). The techniques entail explaining how AI has transformed physicians' ability to diagnose patients by analyzing ECGs. The mentioned algorithms are trained on large datasets by finding underlying patterns without the need for hard-coded rules. A few AI ECG cardiac screening algorithms are also reviewed, with a focus on those that identify several structural and valvular disorders, episodic atrial fibrillation, and left ventricular dysfunction. [31] The assessment indicates that even with the significant advancements in artificial intelligence and the technology applications in cardiac electrophysiology, there can still be unanswered questions that need to be answered. Validation studies to guarantee the accuracy and dependability of AI-assisted illness signature recognition in electrocardiography may be one area where research is still lacking. The review may also suggest that more research is needed to determine whether AI can be used in population-based atrial fibrillation detection, taking into account ethical, economical, and accessibility issues. The promise of extended realities, non-invasive ablation therapy, and robots in EP care may point to the necessity for more investigation into the practical difficulties and therapeutic efficacy of these innovations. [32] The review suggests that even with these encouraging improvements, there might still remain unanswered research questions. Among these would be the requirement for validation studies to evaluate the effectiveness and dependability of AI models in the real world for identifying different phenotypic features and cardiovascular diseases.In [33] the goal of the project was to create a toolbox for Electrocardiography (ECG) analysis with a graphical user interface that is easy to use. The toolkit was made to cover every stage of ECG analysis, from statistical research to the recording device. Furthermore, a novel feature computation approach was put out for ECG analysis with the goal of offering unique information that goes beyond the primary wave amplitudes and durations.In [34] according to the study, compared to MPP followed by a 12-lead ECG, single-time point lead-I ECG devices in primary care may be a more economical use of NHS resources for detecting AF in patients with signs or symptoms and an irregular pulse. [35] The study included 180,922 patients with 649,931 normal sinus rhythm ECGs. The AI-enabled ECG identified atrial fibrillation with an AUC (AUC (Area Under the Curve) measures the ability of a classification model to distinguish between classes, with values closer to 1 indicating better performance.) of 0.87 (95% CI 0.86-0.88), sensitivity of 79.0%, specificity of 79.5%, F1 score of 39.2%, and overall accuracy of 79.4%. When including all ECGs acquired during the first month of each patient's window of interest, the AUC increased to 0.90 (95% CI 0.90-0.91), sensitivity to 82.3%, specificity to

83.4%, F1 score to 45.4%, and overall accuracy to 83.3%. The objective of the study in [36] was to evaluate four distinct approaches to data reduction for continuous ECG data obtained in cynomolgus monkeys during a validation study. Jacketed telemetry was used to collect the data. On various dosing days, the animals were given ascending doses of moxifloxacin after either a vehicle or vehicle treatment. On each dosing day, continuous ECG recordings were made for 25 hours. Four data reduction techniques were then applied: large duration averages (0.5-4 hours), super-intervals (3.5-9 hours averages), 1-min average snapshots, and 15-min average snapshots. In [37] according to the study, smartphones are expanding the use of ECG and arrhythmia detection, enabling a larger population to have access to the technology. The conversation focuses on how smartphone-based solutions, such as Kardia Mobile and ECG Check, are better at detecting arrhythmias than more conventional wearable monitors that are primarily intended for activity tracking. [38] The purpose of the study was to describe and assess a novel automated technique for identifying reversals in the precordial and peripheral leads of ECGs. The method was designed to analyze cable reversals using basic criteria that took into account correlation dependencies between leads. [39] It was shown that automated ECG interpretation software excluded AF with the highest accuracy. It was discovered that, nonetheless, its diagnostic capacity for AF was comparable to that of all medical specialists. In primary care, General Practitioners (GPs) were shown to have a higher specificity of AF diagnosis from ECG than nurses. In [40] the study found that the idea for creating a cloud-based health care system came from recent developments in cloud computing and mobile technology. These systems have the potential to improve accessibility and convenience for medical professionals and patients by enabling the automated gathering and sharing of medical data. In [41] the study found that a useful technique for detecting the QRS complex in the 12-lead ECG was the combination of signal entropy and SVM. In [42] the standard 12-lead ECG is frequently used to diagnose heart disease, but it may not always be the best method, according to the study. Investigation into other techniques, like the examination of high-frequency QRS components, may yield more diagnostic data.

In conclusion, there are a number of research gaps that need to be filled even though ML and DL have the potential to completely transform cardiac arrhythmia diagnosis and ECG analysis. These include the requirement for research on the clinical applications of AI-based ECG analysis, standardized datasets, and validation studies. Closing these gaps will make it more likely that AI will be successfully incorporated into clinical practice to improve cardiac care. This paper fills a research vacuum by examining the need for studies on the practical applications of AI-based ECG analysis with the help of the alerting system and edge based analysis for accessing the health of an individual in short cycles, to find a potential for SCA, and alert them. This prompts an individual at risk to facilitate interaction with their nearest physician and potentially avoid a SCA.

3. Methodology

The aim of any medical detection system is to send alerts and/or detect a potential problem, in our case, the likelihood of a Sudden Cardiac Arrest (SCA). The process begins with the acquisition of data from edge sources, predominantly numeric in nature. The initial phase of data processing involves preliminary data analytics, which includes essential data cleaning and preparation procedures to render the data suitable for further analysis. These data cleaning steps include the elimination of duplicates, rectification of errors, and ensuring consistent formatting of the data [43]. Subsequently, the data is modeled using a Multi-Layer Perceptron (MLP), the architectural details of which are elaborated upon below. The primary objective of the preliminary analytics phase is to determine whether an alert should be triggered.The proposed methodology is seen in Figure 2

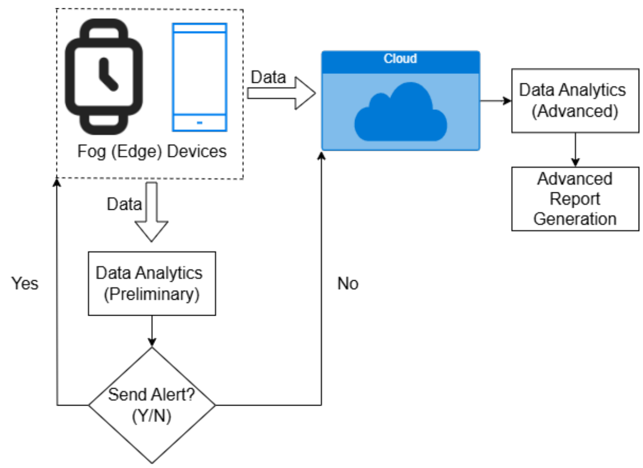

Figure 2. Proposed Methodology

More advanced analytics can be performed at the cloud level on the processed data [44]. We used the 2-lead recordings from the open-source 'INCART 2-lead Arrhythmia Database' for our investigation. A lengthy recording from one lead is used to create a rhythm strip to guarantee an accurate evaluation of the heart rhythm. Lead II is the recommended option for recording the rhythm strip due to its ability to clearly display the P wave [45]. A ECG is seen in Figure 3

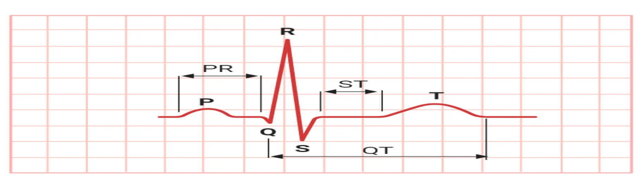

Figure 3. ECG cited from [46]

A. Dataset Preparation

For this project, we utilized the publicly available IN-CART 2-lead Arrhythmia Database, which contains annotated ECG recordings for arrhythmia detection. The dataset consists of recordings from 75 subjects, with each recording spanning 30 minutes. The data was resampled to 250 Hz and segmented into 10-second windows for analysis, ensuring compatibility with real-time processing requirements [47].

B. Feature Selection

The dataset was preprocessed to extract 34 distinct features from the raw ECG signals. These features include time-domain metrics such as heart rate variability (HRV), RR intervals, P-wave morphology, and frequency-domain components derived from a wavelet transform[48]. This approach was chosen to capture both temporal and spectral features of the ECG, enhancing the accuracy of SCA prediction. Recent studies emphasize the significance of feature selection in reducing noise and improving model performance, particularly in edge-computing environments [49].

C. Fog Computing Integration

In this system, fog computing plays a critical role in real-time SCA detection. Preliminary data analytics, including data cleaning (e.g., removing duplicates, correcting errors), is performed at the edge level as seen in Figure **??**. This minimizes the latency associated with transmitting large amounts of data to the cloud for analysis. Essential steps such as feature extraction and preliminary alerting are handled locally to ensure immediate responses, while more computationally intensive tasks, such as advanced data analytics and model refinement, are deferred to the cloud [50]. Fog computing also aids in reducing bandwidth usage and ensures that critical medical alerts can be generated in real time [51]. To simulate fog computing, multi-threading was employed, which allowed multiple fog nodes to operate concurrently. Each fog node operates as an independent thread, processing its assigned portion of the dataset in parallel with other nodes. This ensures that computations are performed concurrently, thereby reducing the overall processing time. The multi-threading setup allows multiple fog nodes to handle tasks simultaneously, efficiently simulating the decentralized nature of fog computing. To account for the variability in real-world network conditions, the system simulated latency and packet loss for each fog node:

- Latency Simulation: For each node, random delays (in the range of 0.1 to 1.5 seconds) were introduced to mimic real-world network latency. This ensured that each fog node experienced variable processing times, simulating different network conditions.

- Packet Loss Simulation: A probability of packet loss (set at 20%) was added. If packet loss occurred, the fog node would skip processing its chunk of data and return no result, simulating real-world packet loss scenarios in edge computing environments.

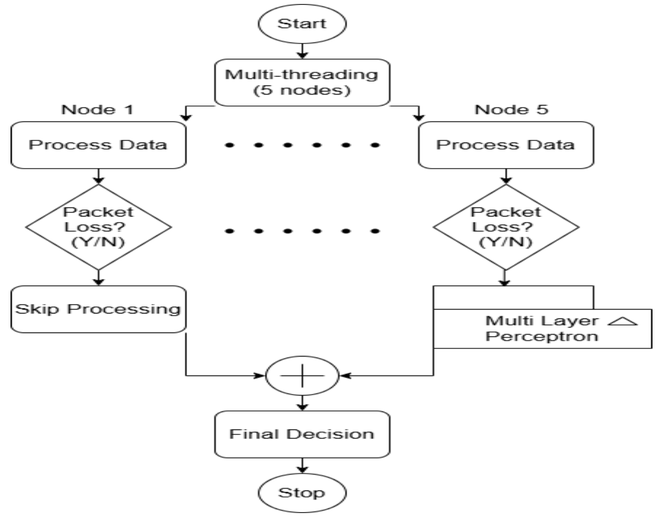

Figure 4. Fog Computing Flow

At each fog node, a neural network model was instantiated to process the data locally. The MLP model was built using Keras and was identical across all fog nodes, ensuring consistent predictions. The nodes performed forward propagation and returned the predictions to the central system, mimicking the real-time processing behavior of fog nodes. The predictions from each fog node were aggregated in real time. This was facilitated by using a shared queue, where each fog node would place its result after processing its assigned data chunk. The results were collected and later combined to form the final decision. This step ensured that all nodes contributed to the overall prediction task, replicating the cooperative nature of fog computing.

D. Model Architecture

The processed data is fed into a Multi-Layer Perceptron (MLP) architecture with five hidden layers. Each hidden layer consists of 100 neurons, selected after performing hyperparameter tuning to balance model complexity and efficiency.

The output layer uses the sigmoid activation function, making the model well-suited for binary classification tasks such as predicting the likelihood of SCA. The training was conducted using the Adam optimizer, with a learning rate of 0.1, which has been shown to provide robust convergence for ECG-based anomaly detection models [52].

The input layer of our model consists of 32 inputs, representing the features used for prediction. The hidden layers consist of 100 neurons each, with the Leaky ReLU activation and only the output layer consists of Sigmoid activation.

Our model employs a MLP architecture with five hidden layers, as shown in Figure 5, each utilizing the Rectified Linear Unit (ReLU) activation function defined as:

$$f(x) = \max(0, x) \quad (1)$$

This choice of activation function is known for its ability to facilitate faster convergence during training. Each hidden layer is composed of 100 neurons, allowing the model to effectively capture the complexities inherent in the dataset [53].

Figure 6. showcases the activation functions used. Furthermore, the output layer of the MLP employs the sigmoid activation function, defined as:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

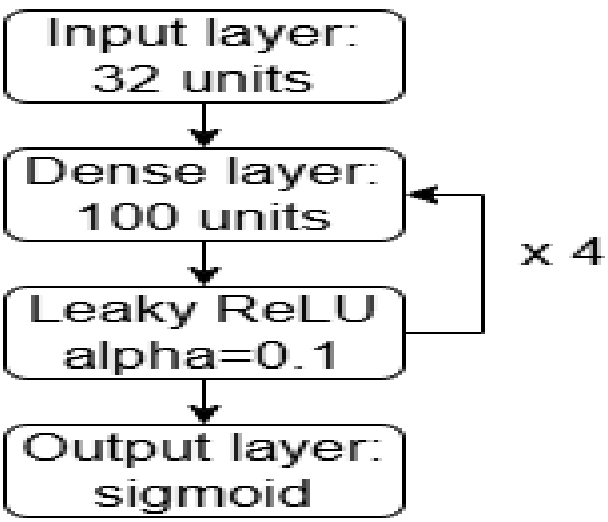

Figure 5. Architecture of Multilayer Perceptron

The input layer of our model consists of 32 inputs, representing the features used for prediction. The hidden layers consist of 100 neurons each, with the Leaky ReLU activation and only the output layer consists of Sigmoid activation.

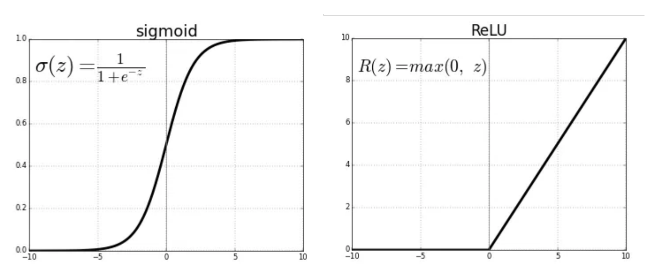

Figure 6. ReLu v/s Logistic Sigmoid cited from source [54]

The sigmoid function maps any real value to the range (0,1), making it particularly suitable for binary classification tasks, as it outputs probabilities, providing a measure of confidence for the prediction of SCA occurrence [55].

E. Evaluation Metrics and Validation

To evaluate the model's performance, we employed metrics such as accuracy, precision, recall, and F1-score, ensuring that the model's predictions align with the clinical significance of early SCA detection [56].

Given the imbalanced nature of the dataset, with relatively few SCA events compared to normal heart rhythms, SMOTE (Synthetic Minority Over-sampling Technique) was applied during training to balance the dataset [57].

4. Results

In order to make precise predictions, the proposed methodology runs each epoch with a batch size of 60. To model 60 readings a minute. The data is processed in batches of 60 rows, with accuracy measured for each batch. Accuracy is defined as the proportion of correct classifications or predictions in each batch.

The graph illustrates how model accuracy evolves with increasing training data. Overall, the graph in Figure 7 reveals that accuracy of the data batches fluctuates between 0.6 and 1.0, with no discernible trend over time. Average accuracy of the proposed model is 99.52%.

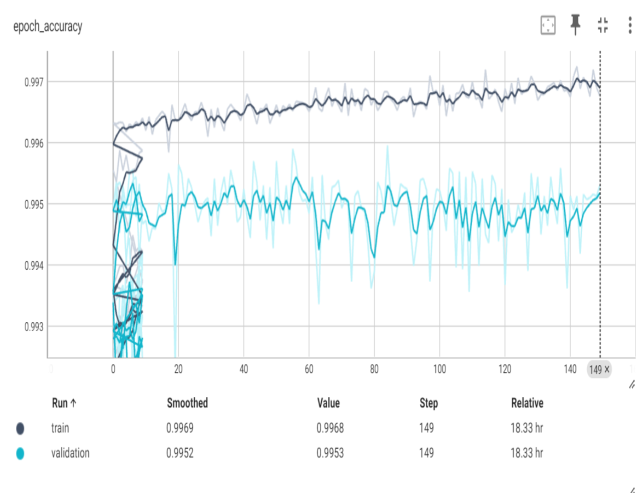

Figure 7. Tensorboard for Accuracy over epochs

The output of the MLP gives the probability of a SCA occurring in the range of 0 to 1, with 1 being the 100% probability of it occurring. Quantifying these occurrences gives us a peek into the possibilities of a SCA as shown in Figure 8

And to ascertain how many individual chances of SCA are predicted in Figure 9 helps with better understanding of the rarity of the occasion. We can safely presume that a SCA is a rare occurrence.

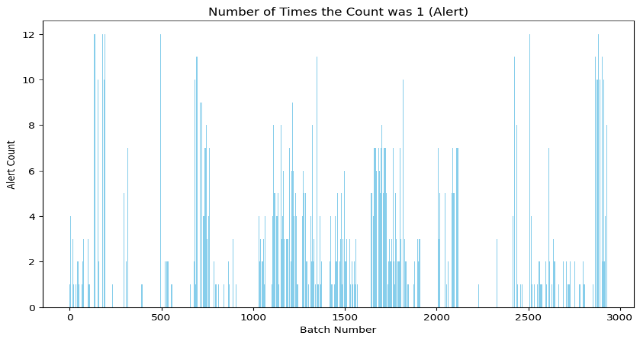

Figure 8. Count of 100% probability of SCA occurrence.

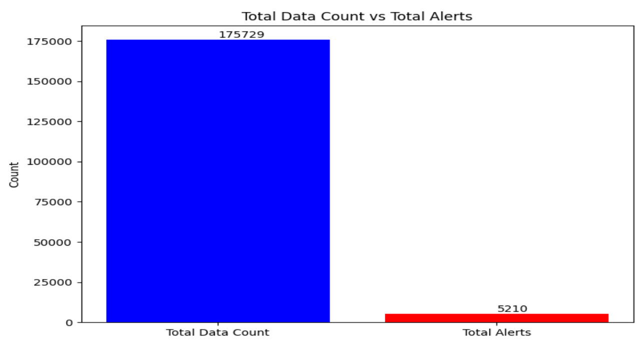

Figure 9. Total Alerts

A. *Classification Report*

Table I is a consolidated view of results.

- **Class 0 (Fog node 0)**: The model has a precision of 0.71 and recall of 0.22, indicating it identifies a fair amount of relevant instances but misses many true positives. This results in a low F1-score of 0.34, reflecting its limited effectiveness in classifying this category.
- **Class 1 (Fog node 1)**: The model performs exceptionally well with perfect precision, recall, and F1-score of 1.00. This class has a large support (30,679), suggesting the model is highly reliable for this class.
- **Class 2 (Fog node 2)**: The model can't make any predictions since no data is received from this node.
- **Class 3 (Fog node 3)**: With a precision of 0.95 and recall of 0.87, this class shows strong performance, evidenced by an F1-score of 0.91, suggesting the model is effective at identifying this category.
- **Class 4 (Fog node 4)**: The model performs almost perfectly with high precision, recall, and F1-score values of 0.99. This indicates it reliably classifies this class, which has a substantial support (4,023).

Overall, the model's accuracy stands at 99.50%, indicating it correctly classifies the majority of instances. The ROC AUC score of 0.80 reflects a good ability to distinguish between classes, as seen in Figure 10.

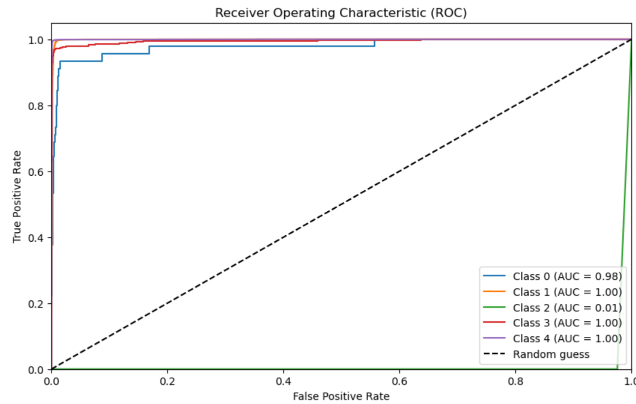

Figure 10. ROC curve

In comparison to existing models, our deep learning approach for arrhythmia detection demonstrates superior performance. Liu et al. (2019) achieved an accuracy of 98.88% with a similar dataset but did not report ROC AUC scores, limiting direct comparison on that metric; our model surpasses Liu's model as seen in [58]. Acharya et al. (2019)[59] implemented various CNN architectures, attaining accuracies between 98% and 99% and high ROC AUC scores, highlighting their strong performance. However, our model's accuracy of 99.50% and ROC AUC score of 0.80 not only matches but slightly exceeds these benchmarks, emphasizing its exceptional capability in multiclass classification tasks. Additionally, Yoon et al. (2019) reported a hybrid model with 99.2% accuracy and an AUC of 0.88, showcasing the benefit of sequential dependencies. Despite this, our model's architecture and activation functions reflect advanced design principles and robust performance, making it highly competitive within the field of ECG classification, as demonstrated by our results compared to Yoon's model in [60].

B. *Fog Computing Results*

Some fog nodes, such as node 2, experienced packet loss, failing to transmit predictions due to common issues like network instability, communication latency, or hardware failures. In contrast, nodes 0, 1, 3, and 4 successfully processed their data chunks from the INCART dataset and returned predictions. The varying processing times (e.g., 0.42 seconds for node 3 and 1.31 seconds for node 4) reflect differences in computational load, resource capacity, and network conditions across the fog nodes. This variation underscores the importance of robust, fault-tolerant models, especially when working with critical datasets like INCART, where delays, failures, or inconsistencies in data transmission can impact the life of an individual. Results are seen in Figure 11.

TABLE I. Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.71	0.22	0.34	45
1	1.00	1.00	1.00	30,679
2	0.00	0.00	0.00	1
3	0.95	0.87	0.91	398
4	0.99	0.99	0.99	4,023
Accuracy			0.99	35,146
Macro Avg	0.73	0.62	0.65	35,146
Weighted Avg	0.99	0.99	0.99	35,146

```
Packet loss at fog node 2
No predictions received from fog node 2 (packet loss)
Received predictions from fog node 3 (processing time: 0.42 seconds)
Received predictions from fog node 0 (processing time: 0.85 seconds)
Received predictions from fog node 1 (processing time: 1.28 seconds)
Received predictions from fog node 4 (processing time: 1.31 seconds)
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Figure 11. Fog computing model predictions output (5 nodes)

5. Discussion And Future Work

This work addresses a crucial research gap by exploring the practical applications of AI-based ECG analysis, particularly in the realm of edge-based analysis and warning systems for short-term health assessment. Our primary objective is to identify individuals at risk for Atrial Fibrillation (AF) and promptly alert them to seek medical attention, thereby potentially preventing Sudden Cardiac Arrest (SCA). We employed a methodology that processes data in batches of 60 rows, calculates accuracy for each batch, and progressively trains the model with increasing data to monitor changes in accuracy. The architecture of our Multilayer Perceptron (MLP) model, featuring five hidden layers with ReLU activation functions and a sigmoid activation function in the output layer, is adept at capturing complex data relationships, resulting in an impressive average accuracy of 99.5%. Our findings highlight the potential of deep learning (DL) in predicting SCA risk, as evidenced by the model's probability predictions ranging from 0 to 1. Although accuracy varied between 0.6 and 1.0 across different data batches, the analysis showed no significant temporal patterns. This variability underscores the inherent rarity of SCA incidents and the need for precise and timely detection methods. Our research contributes valuable insights into the practical applications of AI-based ECG analysis, emphasizing its potential to enhance cardiovascular health monitoring and emergency care.

However, several challenges remain. Ensuring data privacy and security is paramount, given the sensitivity of health information. Establishing robust security measures is crucial to protect patient data from unauthorized access and breaches. Additionally, optimizing resource allocation in edge and fog computing environments is vital for real-time data processing. Efficient resource management can significantly impact the performance and scalability of AI models, ensuring timely and accurate ECG analysis. Future improvements should focus on validating the effectiveness of machine learning models in real-world scenarios to confirm their reliability and efficacy in clinical settings. Collaborative efforts among healthcare providers, technology developers, and regulatory bodies are essential to set standards and guidelines for deploying AI-based ECG analysis technologies. By addressing these challenges, stakeholders can facilitate the successful integration of these transformative technologies into healthcare systems.

6. Conclusion

To sum up, this study significantly contributes to the growing body of research on AI-based ECG analysis, illustrating how advanced technologies like Deep Learning (DL) and fog computing can enhance emergency medical care and cardiovascular health monitoring. By leveraging edge-based analytics and a Multi-Layer Perceptron (MLP) model with an impressive accuracy of 99.5%, our research demonstrates the potential of AI to revolutionize the early detection of Sudden Cardiac Arrest (SCA) and improve patient outcomes. Our findings highlight the capability of DL models to predict SCA risk with high precision, showcasing a model that effectively handles real-time data processing and provides timely alerts. This approach addresses critical challenges in SCA management, such as the need for rapid response and accurate detection, potentially reducing mortality rates associated with cardiac emergencies. Future investigations should focus on expanding use cases to include broader applications of AI in cardiac care, such as real-time monitoring systems and personalized treatment strategies. Additionally, addressing issues related to data privacy, security, and resource optimization in edge and fog computing environments will be crucial for the successful deployment of these technologies.Collaborative efforts among healthcare providers, technology developers, and regulatory bodies will be vital in establishing standards and guidelines for integrating AI-based ECG analysis into healthcare systems. Clinical trials and expanded applications will help refine these models and ensure their practical utility, ultimately advancing our ability to manage and prevent SCA and other cardiovascular conditions.

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