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A Machine Learning and Internet of Medical Things Framework for ECG-Based Heart Disease Diagnosis

Shivashankar[1], Md Shohel Sayeed[*2], Andrews Samraj[3], Manjunath R[4], Sowmya Naik P T[5], Surendra MS[6], Manjunath C R[7]

[1]Postdoc Fellow, Multimedia University, Malaysia, Global Academy of Technology, India.
[*2]Centre for Intelligent Cloud Computing, CoE for Advanced Cloud, Faculty of Information Science and Technology, Multimedia University, Jalan Ayer Keroh Lama, Bukit Beruang, 75450 Melaka, Malaysia.
[3]Department of Computer Science and Engineering, KGiSL Institute of Technology, India.
[4]Postdoc Fellow, Multimedia University, Malaysia, R R Institute of Technology, India.
[5]Department of Computer Science and Engineering, City College of Engineering, India.
[6]Department of Computer Science and Engineering, R R Institute of Technology, India.
[7]Department of Computer Science and Engineering, Global Academy of Technology, India.

ABSTRACT: Cardiac arrhythmia is a major global health concern, and conventional electrode-based Electrocardiogram (ECG) monitoring cannot continuously track drivers, limiting early detection of heart-related risks that could cause road accidents. This study presents a Cardiac Health Assistance System (CHAS) combining Internet of Medical Things (IoMT) sensors and Machine Learning for continuous, real-time cardiac monitoring and diagnosis of vehicle drivers. Wearable ECG and physiological sensors capture heart rate, ECG signals, and driver demographics (age, sex, height, weight), wirelessly transmitted via a multi-layer IoT architecture to a cloud platform. After preprocessing, feature extraction, and labelling, a two-stage classification pipeline evaluates combinations of Naive Bayes, weighted K-Nearest Neighbors (KNN), Decision Tree, and Support Vector Machine classifiers, benchmarked against Long Short-Term Memory (LSTM) and a Fuzzy Inference System-LSTM (FLSTM) model using five-fold cross-validation on 9,200 samples. The best two-stage configuration, Naive Bayes followed by SVM, achieved an F1-score of 94.8 percent and 92.5 percent accuracy at the first stage. Across varying training-data proportions, CHAS consistently outperformed LSTM and FLSTM, reaching an overall precision of 96.30 percent, accuracy of 97.35 percent, and F1-score of 95.77 percent. CHAS showed superior and more stable performance than existing LSTM and FLSTM approaches across all evaluated metrics and data sizes, confirming its ability to reliably detect cardiac abnormalities while minimizing false positives and negatives, supporting timely driver alerts. The proposed IoMT and Machine Learning-based CHAS offers an effective, real-time solution for continuous cardiac monitoring of vehicle drivers, improving road safety through early detection and immediate intervention for cardiac disorders.

1. INTRODUCTION

Cardiac arrhythmia is a serious concern to human health, and it impacts a huge population worldwide. The detection of irregular arrhythmic patterns of cardiac activities is essential for proper intervention. In this proposed research work, we aim to design a comprehensive system with robust abilities for cardiac arrhythmia detection with a potential to classify arrhythmia into thirteen different forms. The data set chosen for this research work connects the essential information for patients, such as age, sex, height, weight, duration of QRS, duration of QT interval, T-wave, and finally a diagnosis. This work proposes a holistic description of the patient's physiological characteristics, which is paramount for the precise identification of arrhythmias. The input variables are crucial for clarifying the linkage between data regarding a patient's demographics, physiology, as well as the development of cardiac arrhythmia. Age, gender, height, and weight are primary variables that may have an electrical activity effect of heart, while duration of the QRS wave, QT wave, T wave are primary indicators for the diagnosis of arrhythmia. The main goal of this research work is to design a analytical model that can tap into the immense data source at hand for classifying arrhythmias. The benefit of this predictive model is that it will not only serve in early diagnosis for problems of arrhythmia but also create pathways for developing personalized treatments, targeted at specific individuals' reports. The simulation outcome validates the hypothetical analysis and plays the effectiveness of proposed approach. During ongoing investigations, image analysis, for instance, MRI or CT, has so far been applied to classify and prediction of analytical sequelae in stroke patients. Not entirely are these ideas challenging to analyze right off the bat progressively, however they likewise have constraints as far as a long test time and a significant expense of testing.

The majority of this involves the driver's Electrocardiogram (ECG) signal and classification. The first step in the acquisition of an ECG signal is the introduction of an algorithm that uses the steering wheel of the car to extract signal of ECG from driver. When the driver is shown the user interface and the interaction between the instruments used for data collecting and analysis. This is then followed by the introduction explaining the mechanism of the heartbeat generation in the human heart. Every heartbeat in the human heart is shown on the ECG using the wave arm. The existing system primarily detects cardiac arrhythmia, relies on traditional ECG monitoring methods, which involves the use of electrodes placed on patient's skin to record electrical activity. Limitations in terms of continuous monitoring and real-time detection are conventional ECG devices are not integrated with IoT sensors, which restricts the ability to capture additional vital parameters such as age, sex, height, and weight. The data preprocessing methods used in the current system might not be able to fully utilize the capabilities of sophisticated machine learning models. The accuracy and efficiency of arrhythmia detection can therefore be improved. uses machine learning methods to accurately classify cardiac arrhythmias. This highlights the need for a more complete and real-time solution that uses cutting-edge machine learning techniques to accurately classify cardiac arrhythmias and combines IoT devices for improved data collections. The system sends Information about the condition of patient to near hospitals or care for early treatment. This System sends information about the health of the vehicle drivers to the nearer hospitals or to their caretaker.

In this research work, it suggests a car steering wheel system for single-lead ECG measurement to gather driver's data in noisy environments [1]. An algorithm is introduced to assess if the driver maintains a stable grip based on ECG and heart rate signals. This review suggests Machine Learning (ML)model to categorize driver's heart related health condition and a single lead ECG estimate framework used to control the vehicle's wheel. Together with the estimation equipment, a calculation to obtain a steady ECG signal is suggested for the ECG estimation framework. In order to determine strength in noisy situations caused by vehicle vibration, it uses the time frame ECG signal. To categorize four types of heart conditions (typical, atrial fibrillation, various rhythms, and clamour), a two-stage ML algorithm is suggested.

The organization of the research article is as follows: Section 1 describes the introduction of ECG monitoring and heart disease diagnosis system for vehicle drivers using IoT and Machine Learning algorithms. Section 2 designates some research related work about ECG monitoring and heart diseases. Section 3 presents the cardiac health assessment system design and implementation using IoT and Machine Learning algorithms. Section 4 describes the performance comparison of our model with Long Short-Term Memory (LSTM) and Fuzzy Inference System (FIS) with Long Short-Term Memory (FLSTM).

2. LITERATURE REVIEW AND RELATED WORK

This study proposes a medical decision support system for heart failure diagnosis using 3-lead ECG, a cost- effective and readily available tool. Unlike expensive and sometimes invasive tests, ECG offers a quick initial assessment for identifying heart failure types (HFrEF and HFpEF) [2]. The system aids doctors, especially in emergency cases, saving time and costs by avoiding unnecessary tests. This approach aims to address the challenge of diagnosing heart failure efficiently with simple and accessible technology. The ECG is clearly used to identify HF subtypes. All patients with heart related disease should have echocardiography and it is expensive and necessitates subject matter experts. Indeed, even in high-asset locales, this test is not generally performed, and treatment should be started before the echocardiographic information are gotten. For such circumstances, prudent and functional frameworks are required.

Insomnia is a typical rest problem wherein patients cannot rest as expected. The critical first step in the early stages of a mental illness investigation is the accurate detection of sleep deprivation muddle. One of the main causes of cardiovascular diseases, such as circulatory strain and stroke, is the disruption of getting enough sleep. According to P. Tripathi *et al.* [3], the traditional methods for identifying sleep disorders are laborious, inefficient and more exclusive because they require a trained neurophysiologist for a considerable amount of time and are disposed to to human error. As a result, accuracy of the results is compromised. This study suggests that sleep disorders can be identified based on ECG signals, making it reliable and implementable in embedded hardware. Atrial fibrillation in the elderly may influence Heart Rate Variability (HRV) analysis, but HRV can still assess autonomic dysfunction. The research also introduces the ML method for insomnia detection using single sleep ECG recordings. The LDA classifier showed the highest accuracy (99%), making it is undertaking tool for detecting insomnia and its stages. The authors of the research [4] investigate a cognitive radio network where a minor transmitter with the energy-harvesting device resourcefully accesses the main channel. The system achieves both energy and spectrum efficiency by optimizing spectrum sensing and energy harvesting. The study takes energy and collision limits into account while determining the best parameters, such as the detection threshold and energy harvesting rate. This paper introduces a system analyzing elderly health using real-time ECG and PPG signals collected during daily walks [5]. A ML model predicts stroke symptoms with over 90% accuracy. The proposed system, wearable with minimal inconvenience, has significant potential for practical healthcare services by monitoring and preventing stroke incidents. Future studies will expand analysis to include additional bio-signals and medical information for a more comprehensive approach.

The model depicts both customary time/recurrence space and high-level AI strategies revealed in the distributed writing at each phase of examination, beginning with ECG information securing to its characterization for the two constant observing frameworks by M. Wasimuddin *et al.* [6]. We present an extensive survey of continuous ECG signal obtaining, prerecorded clinical ECG information, ECG signal handling and denoising, location of ECG fiducial focuses on view of component designing and ECG signal order alongside similar conversations among the explored examinations. The authors has discussed a stages-based model for deciphering ECG-related literature, focusing on problems and proposing areas for future research. An extremely quick technique that can extract and separate features is an extreme ML based on local receptive fields. The Fuzzy Inference System (FIS) with Long Short-Term Memory (FLSTM), a well-liked type of recurrent brain organization architecture demonstrated exceptional performance with respect to time processing domains [7]. In this paper, they proposed DELM-LRF-BLSTM is an emerging technique that integrates the use of the ELM-LRF method with FLSTM networks for the 99.32% accuracy and 97.15% sensitivity on the MIT-BIH Arrhythmia dataset, outperforming other methods with low computational complexity. The high speed of ECG recognition has fostered its application in automatic arrhythmia diagnosis. In the future, the focus will be on improving the accuracy of recognition using methods such as dimension reduction and de-noising, ensuring timely and efficient arrhythmia detection, potentially providing life-saving outcomes.

The architecture includes a front-end IoT-based device [8], a cloud information dataset, a simulated intelligence level for diagnosing heart illness, and an application user interface for the smart device. ECG signals can be recognized by the IoT-based device, a wearable ECG solution that comprises a basic Bluetooth module. Based on input from cardiologists, it employs a streamlined algorithm to identify heart rhythm problems [9]. The objective is to simplify the model and implement it on chips for widespread heart disease detection and health monitoring; more varied data is required to increase accuracy. Use case analysis is used to determine dataset limits. Three distinct use cases are developed in consideration of various application scenarios using ECG-based verification [10]. The accuracy of ML-based ECG biometric confirmation systems increases when more qualified preparation data is used to compare AI conspiracies. This paper presents the ML system for biometric authentication based on ECG. Given the widespread usage of portable and connectable ECG equipment, the framework aims to increase user authentication accuracy [11]. Time slicing for high-quality ECG datasets, three authentication categories, new pre-processing methods, data quality measures, and a MATLAB Toolbox are all included. his framework helps in the design and analysis of ECG authentication using the ML approach [12].

A responsiveness beat family classifier, consisting of sign preprocessing modules and a straightforward k-Closest Neighbor classifier, was designed with the responsiveness of the subblocks in mind. As is customary in earlier research on the subject, the MIT-BIH Arrhythmia database was utilized for this purpose. Two implementations were employed: one for multiclass beating label assignment and another for bi-class order (supraventricular vs. non-supraventricular on-start). It is important to exercise caution when using machine learning algorithms in the medical field, particularly when it comes to beating pattern recognition [13]. Working together with cardiologists is crucial, and methods like out-of-sample training could be used. It is important to address the problem of class imbalance in beat categorization, and databases like MIT-BIH arrhythmia should be used with caution. Digital signal processing stages should be considered alongside ML. Resampling tests are proposed for practical ML system design and performance evaluation in beat family detection. The framework that predicts the individual for the problem first is a benefit to the earth. It tends to be accomplished with by the headway in the innovation for the current and past arrangement of patient observing. Signal handling is huge well-known frameworks for the examination of ECG. Numerous methods have been produced for ECG examination however enhancement calculation has not been utilized in the current work [14]. The use of advancement is important to standardize the signs to work on the exactness. This study introduces an optimization algorithm for ECG analysis, enhancing accuracy.

In proposed [15] work, an ear-worn system for BP and heart rate monitoring with high wearability are pbserved. Sensors are racked up at the sides of the ears. Ear-ECG/PPG signals are picked up on the bio-potential platform. This work presents the usage of the classification system on raw heartbeat identification and the purification of distorted heartbeats. Heart rate and blood pressure monitoring frameworks have been shown to demonstrate the best performance using ECG classifier device. The paper clearly proves the practicability of wearable ECG/PPG solutions based on the ear for a continuous health monitoring service, hopefully to optimize power consumption in the forthcoming work. This algorithm classifies in paper [16] AF and other rhythms from short-term signals, using both machine learning and simple methods. It prioritizes specificity, with low sensitivity. A hybrid QRS detection method improves overall F1 score. The algorithm, suitable for mobile diagnostic devices like AliveCor, shows promise in wide arrhythmia classification.

The authors have suggested [17] a stable biometric ECG acknowledgment method with a constant cycle location system and examination computation to operate on different device/application security and wellness monitoring. This research reports novel remote innovation and procedures that can function on the presentation by using simple and low-cost draws near, in contrast to previous work on wearable ECG acknowledgment that was based on cabled non-remote frameworks [18]. This paper has introduced a new and effective ECG recognition method with a low Equal Error Rate of 0.98%. Despite the reduced number of participants, the efficiency of the algorithm is appreciable, using sophisticated methods such as the Neighborhood Search algorithm and the Cyclic Rotation Metric in optimal distance score comparison [19]. It is difficult to design an efficient cardiac health information system because of the different ECG descriptors and the continuous monitoring required [20]. With minimal computer complexity, it effectively detects arrhythmias. More tests are planned in the future to evaluate reactivity to noise and account for interconnected ECG characteristics [21].

The dataset has various heart beats, and three methods were used to classify them. The accuracy rates for knowledge-based, ANFIS, and rule-extraction approaches are 90.24%, 94.13%, and 95.98%, respectively. These techniques, particularly the rule-extraction method [16-18], are excellent at differentiating between various beat kinds [22]. The suggested study aims to create a model that can estimate understudies' SGPA based on attributes. It forecasts the results as SGPA of software engineering students using their prior academic performance [23], research, and personal inclinations during their academic using multiple Computer-programmed analytical devices are needed for ECG signal grouping since the growing patient population is destroying the characterization result when taking into account notable variations in the ECG signal examples among different patients [24]. It is seen that heart failure or cardiovascular illness for the most part foster after sometimes however is difficult to find because of the absence of information and innovation, generally in emerging nations [25]. One of the primary causes of this high passing rate, despite being avoidable, is a lack of hardware and participation. There has been a lot of interest in using this breakthrough in medicine due to the enormous scientific and inventive advancements in artificial brain networks area. The authors [26] depict the most recent advancement in pulse sensors engaged by AI strategies.

The joining of an Adafruit ILI9341 LCD screen gives ongoing visual criticism of the bioelectrical signs and framework status to the client. The IoT viewpoint is acknowledged through the ESP32's Wi-Fi module which empowers the transmission of the handled bioelectrical signal information to a cloud server [27]. This arrangement takes into consideration remote observing and information investigation. We provide a distributed network multiscale ECG framework to show how computational burden and time associated with flexible ML could be reduced [28]. This design identifies a few clinically important ECG components by doing a restricted analysis of ECG waveforms locally on a PDA. To ascertain each person's "unique finger impression" premise designs and spot irregularities in those examples, a flexible machine learning motor is situated on a remote server. One of the main causes is the real distance between the patient and the facility [29]. This paper concentrates on the applying of IoT in medical care space and a framework is wanted to notice the ECG of the far-off understanding [30]. The excellent and sensible medical care is increasingly more popular to fulfill the necessities of the developing human populace and clinical costs. IoT has fundamentally had an impact on the way correspondence happens close by information assortment sources supported by sensors introduced by Muhammad Umer *et al.* [31]. It additionally has conveyed Artificial Intelligence techniques for better dynamics given by proficient information assortment, capacity, recovery and information the executives.

3. DESIGN OF CARDIAC HEALTH ASSISTANCE SYSTEM

This research study aims at designing an Internet of Things (IoT) based Electrocardiogram (ECG) monitoring and heart disease diagnosis system, particularly designed for vehicle drivers. The device combines wearable ECG sensors, wireless communication modules and cloud analytics to record and analyze physiological data. Machine Learning (ML) algorithms are used to analyze ECG signals, extract their relevant features and determine possible heart disorders. Using by offering alerts and insights, the proposed system improves the safety of the driver and enables them to arrive early. It also aids in the detection of risks associated with the heart, as it reduces the occurrence of road accidents resulting from a sudden cardiac event. The Cardiac Health Assistance System (CHAS) is proposed to be an intelligent real-time healthcare monitoring system with a focus on early diagnosis, continuous evaluation and immediate intervention for cardiovascular diseases. The proposed system combines wearable sensors, IoT technology and edge-cloud computing techniques to proposed CHAS for patients and professionals. Data collecting, communication, processing, and application are among the layers that make up the multi-level architecture of the suggested system. Biomedical sensors, such as wearable and embedded sensors, are the main component of the data collecting layer. Physiological factors like body temperature, blood pressure, heart rate, ECG, and blood oxygen level (SpO_2) can be continuously measured using these sensors. The sensors are designed to function with lower power consumption and greater sampling accuracy for uninterrupted sensing and monitoring. The communication layer utilizes trusted wireless communication techniques such as Bluetooth Low Energy communication, WiFi, or 5G networks for effective wireless communication of sensor values to edge or gateway devices. The MQTT and CoAP message queuing communication techniques are used in this layer for trusted and efficient communication with lower latency. The CHAS system also incorporates end-to-end encryption techniques to safeguard highly sensitive patient information during communication.

The Long Short-Term Memory (LSTM) layer is conceptualized as a sequence processing layer of a neural network, characterized by weight matrices and states that are updated at each time step using differentiable operations. From an implementation point of view, an LSTM is a parameterized recurrent module of a neural network that performs vectorized computations of gates, state transitions, and learning using gradients. The Fuzzy Inference System with Long Short-Term Memory (FLSTM) is a hybrid approach that integrates fuzzy logic-based reasoning and deep sequence learning to address uncertainty, nonlinearity, and time dependency simultaneously. From a technical point of view, FLSTM is a fusion of fuzzy rule-based feature transformation and LSTM's recurrent processing.

3.1 Overview of the Cardiac Health Assistance System

Encompasses a comprehensive framework for real-time cardiac arrhythmia detection utilizing IoT sensors. This proposed CHAS encompasses a complete framework for real-time cardiac arrhythmia detection utilizing IoT sensors. These sensors will be strategically deployed to capture essential physiological parameters, including age, sex, height, weight, QRS duration, QT interval, and T wave morphology. Collected data undergoes preprocessing. Subsequently, a CHAS multi-class classification model will be developed, leveraging advanced algorithms and ML architectures to accurately classify arrhythmia into thirteen distinct categories. These data set are collection for maximum blood pressure, ECG, and heart rate, and they are fed member functions that are fuzzified into fuzzy sets using a fuzzy value range. The operation of fuzzy information system for predicting risk of heart related disease is shown in Figure 1.

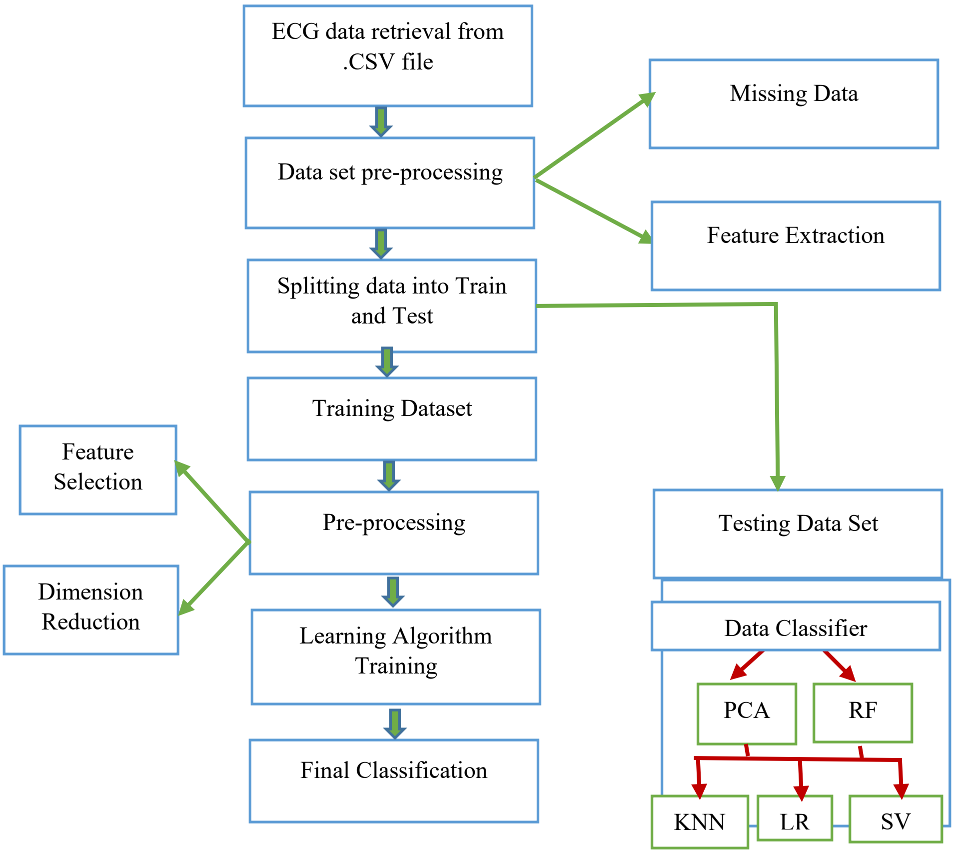

Figure 1. Block diagram of Cardiac Health Assessment System and prediction.

3.2 Data Flow Diagram of Cardiac Health Assessment System

Figure 1 shows data is input into the system, data is produced from the system, various forms of data flow through the at a system, and data storage. It doesn't contain information that is presented sequentially, simultaneously, on process time, or in opposition to a normal structured flowchart that shows how activities will control flow, and a Unified Modelling Language activity workflow diagram that shows how control and flows are emphasized as one cohesive unit from the model. The data is extracted from the CSV file, and the dataset is further processed. The art of digital signal processing in electrocardiography involves filtering the recorded signals since genuine ECG data is signals generated by breathing categorical data encoding and separating the noisy and contaminated.

The implementation of CHAS process involves several crucial steps. Firstly, data pre-processing is essential to handle missing values and normalize the raw data in order to prepare it for analysis. Data labelling then assigns meaningful tags or categories to instances, allowing the conduct of supervised learning tasks. Feature extraction is the distillation of raw data down to a concise set of informative features. In classification, various algorithms will therefore categorize the data using these features. Lastly, evaluation will look at the model's performance through metrics such as accuracy or F1- score to ensure the model is effective and reliable for real-world applications.

On test and train information, a Self-Getting Sorted Out Map (SOM) is applied first, and the result is funneled into a classifier that utilizes Learning Vector Quantization (LVQ). The adjoining its neuron's learning rate weight (W) update rule in SOM is W_i(t + 1).

$$W_i(t+1)=w_i(t)+\eta_{ci}(t)\{x(t)-w_i(t)\} \quad (1)$$

$$Z=argminj(x(t)z_i(t)) \quad (2)$$

$$Z_c(t+1)=[1-s(t)\alpha c(t)]z_c(t)+s(t)\alpha c(t)x(t) \quad (3)$$

A Fuzzy Inference System (FIS) is used to categorize risk of heart disease based on patient wellbeing data, and the methodology is presented as the CHAS algorithm. Algorithm: Cardiac Health Assessment System (CHAS) for Ensuring Safe Driving Through IoMT and Machine Learning Application of trained Machine Learning model for classification of cardiac diseases.

Algorithm1: Cardiac Health Assessment System

Step -1: Input:

ECG signals obtained from wearable biosensor, demographic attributes of the driver (Age, Sex, Height, Weight), and identification attributes of the car.

Step-2: **Output:** Cardiac status of the driver (Normal/Abnormal), real-time notifications, alerting, and health record on the cloud.

Start

Initialize IoMT-enabled wearable ECG sensor and vehicle monitor.

Step-3: Register driver details:

- *Driver ID*
- *Age*
- *Sex*
- *Height*
- *Weight*
- *Emergency contact information.*

Step-4: Continuous acquisition of ECG signals through the wearable biosensor.

Step-5: Collection of more physiological and demographic data parameters.

Step-6: ECG Signal Preprocessing:

- *Filtering for removal of noise and motion artifacts.*
- *Normalization of signal amplitude.*
- *Segmentation of ECG beats.*

Step-7: Feature extraction from the ECG signal:

- Heart Rate
- RR Interval
- Duration of QRS Complex
- PR Interval
- QT Interval
- Characteristics of P-waves

Step-8: Heart Rate Variability (HRV) Features.

Step-9: Formation of Feature Vector by using:

- ECG features, and
- Driver demographic parameters.

Step- 10: Transfer of the formed feature vector to the cloud platform via low power IoMT communication interface.

Step-11: Deploy the developed Machine Learning algorithm for classifying heart diseases:

Input: Input vector.

Output: Normal or Abnormal heart condition.

Step-12: In case of Normal output, then:

- Save the output in the cloud database.
- Proceed with real-time tracking.

Step-13: Otherwise, in case of Abnormal output, then:

- Determine the severity level of the detected abnormality.
- Issue an instant alert to the driver via car dashboard.
- Inform subscribed users and emergency contact person.
- Provide the driver's health information to relevant healthcare professionals.
- Advise on taking medical consultations remotely or immediately.

Step-14: Save all ECG signals, outputs, alerts, and actions in the cloud database.

Step- 15: Loop Steps 4 to 13 during the entire duration of driving.

End

Table 1. Simulation parameters settings

Parameter	Value
Total samples	10,400
Number of arrhythmia classes	15
Patient attributes	Age, Sex, Height, Weight
ECG-derived attributes	QRS duration, QT interval, T-wave morphology
Train/test split	88% trained data
Cross-validation	4-fold
Large-scale comparison dataset	100000 records

Simulation settings for the proposed Cardiac Health Assistance System (CHAS) were set according to the following parameters shown in Table 1. The test data contains a total number of 10,400 samples that correspond to 15 different types of arrhythmia. Thus, the label space can be considered sufficiently varied for the multi-class classification stage. Each sample possesses two types of attributes. The first type includes patient demographic attributes (Age, Sex, Height, and Weight) that provide physiological variation within the driver population. The second type includes electrocardiogram derived attributes (QRS duration, QT interval, and T-wave morphology).

4. RESULTS AND DISCUSSION

In CHAS simulated environment, we emulated real-world scenarios where vehicle drivers wore the proposed wearable sensors integrated with the cardiac health assessment system. Synthetic physiological data simulating heart rate, blood pressure, and ECG signals were generated to represent varying health conditions and potential cardiac abnormalities. Upon implementing the pseudo code provided, the system effectively collected, pre-processed, and analysed the simulated physiological data in real-time. Machine Learning algorithms can identify anomalies and warning signs for potential heart irregularities with a high degree of efficiency. During the simulation, the results showed that the system was able to successfully send notifications to drivers or concerned authorities for every abnormal pattern that was identified, hence the capability to improve safety on the road for drivers. The results of this simulation confirm the efficiency and effectiveness of the CHAS for vehicle drivers using IoT and Machine Learning. The continuous capability of the proposed solution to monitor drivers for cardiovascular irregularities and predict outcomes is an important aspect of improving public health conditions on the road.

The two-stage classification technique is used by Naïve Bayes, weighted KNN, Decision Tree and Support Vector Machine classifiers. A total of sixteen potential two-stage classification systems can be developed by combining these four models during the two classification stages. In both classification stages, the selection of the best relevant features is made by training and testing the classifiers with ever-increasing numbers of potential features, selecting those that provide the best possible results for the classifiers. For class balance to be maintained, 86% of the 9,200 samples are used for training, and the remaining 27% are used for testing, with evaluation conducted over five-fold cross-validation. The best possible F1-measure of 94.8% is attained by a two-stage classification process that combines a first-stage binary classification Naïve Bayes and a second-stage multi-class classification SVM. For the first-stage Naïve Bayes binary classification, ten features are chosen, and the accuracy attained is 92.5%.

4.1 Comparative Analysis

CHAS is measured by how carefully it aligns with improvements in informational indices related to coronary artery disease. In the request for increasing accuracy, Table 1 lists the correlation study that breaks down the precise results of the CHAS models. Figures 2, Figure 3 and Figure 4 represent the correlation of the exhibition consequences of the CHAS model with the current frameworks. The aftereffects of the assessment with the connected best in class coronary illness prescient frameworks find out that the CHAS exhibition outperforms that of the current frameworks.

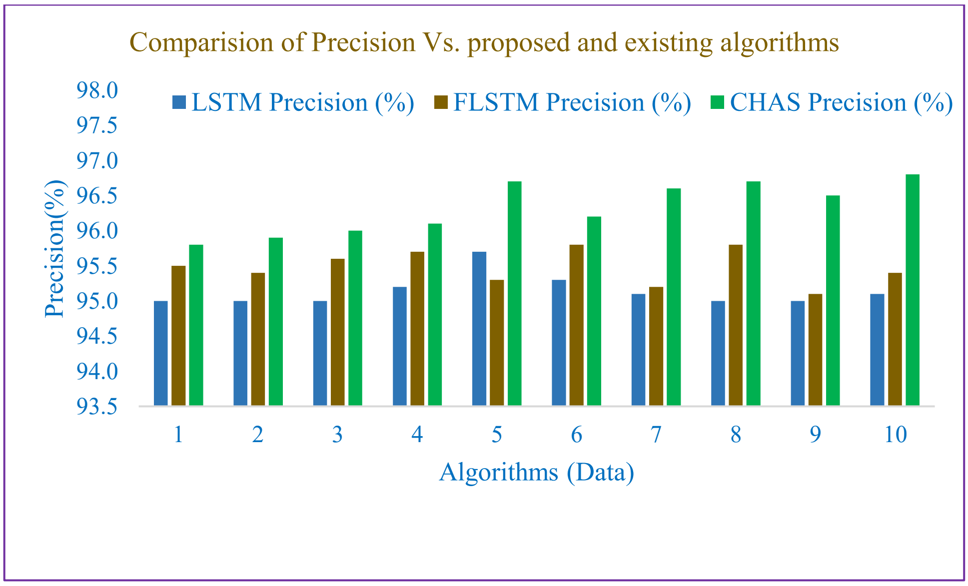

Figure 2. Performance result evaluation of Precision vs. data.

In Figure 2, the effect of the increasing size of the training dataset, varying from 10% to 100%, on the precision of the three models, LSTM, FLSTM and CHAS, is shown. As the size of the dataset increases, the precision of all models remains uniform. Out of the three models, CHAS model has the highest precision irrespective of the size of the dataset, which demonstrates the capability of CHAS to accurately detect the actual cardiac anomaly without generating any false positives data. The precision of the FLSTM model is slightly better than that of the LSTM model, this illustrates the efficiency of the advanced filtering of features in the FLSTM model.

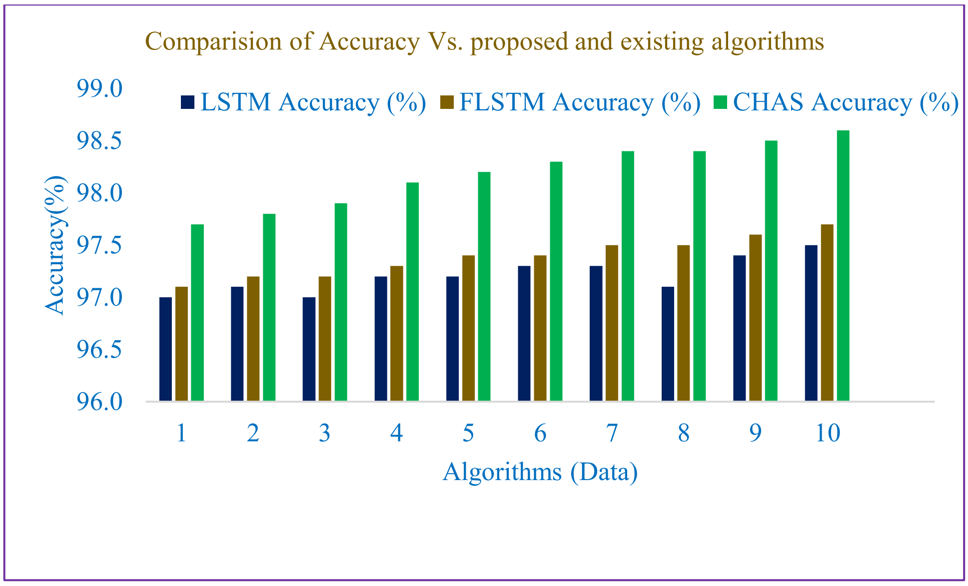

Figure 3. Performance result evaluation of Accuracy vs. data.

Figure 3 demonstrations of how the accuracy of models using LSTM, FLSTM and CHAS changes with the increasing amount of available training samples. There is a steady increase in accuracy for both models, thus reinforcing the idea that increasing the number of samples available improves learning efficiency and effectiveness. The CHAS model indicates a consistently high degree of accuracy, irrespective of the size of samples available, thus clearly outperforming other models in this aspect. Figure 3 not only proves that CHAS has better heart disease prediction accuracy, but there is also a considerable difference with increasing sample size.

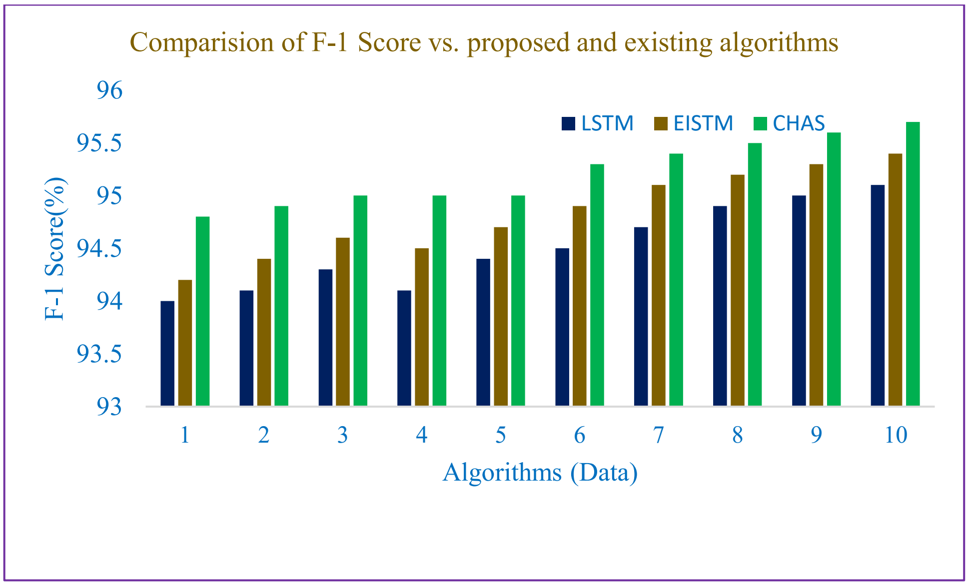

Figure 4. Comparison results of the overall performance metrics.

The experimental implementation using Python programs are performed with models of conventional LSTM and FLSTM models for coronary disease risk expectation utilizing CHAS ECG health risk dataset with 10,00,00 records. The precision of the conventional LSTM model is 95.232%, which the FLSTM outperforms with 95.331% precision. The proposed framework with FIS joined with LSTM beats the two past models with 96.887% precision. Figure 4 shows the overall performance of the proposed model CHAS and other existing models LSTM and FLSTM models. The CHAS model framework additionally presents the further developed brings about terms of precision, accuracy and F1 Score.

Table 2. Performance measures of metrics in ECG monitoring and heart disease diagnosis system for vehicle drivers using IoT and machine learning.

Data (%)	Precision (%)			Accuracy (%)			F1 Score (%)		
	LSTM	FLSTM	CHAS	LSTM	FLSTM	CHAS	LSTM	FLSTM	CHAS
10	95.06	95.12	95.88	96.09	96.13	96.53	94.12	94.26	95.07
20	95.07	95.15	95.92	96.12	96.29	96.88	94.18	94.34	95.22
30	95.08	95.20	96.03	96.33	96.43	97.13	94.22	94.47	95.45
40	95.17	95.24	96.11	96.36	96.55	97.25	94.25	94.53	95.58
50	95.24	95.27	96.15	96.51	96.89	97.33	94.30	94.63	95.78
60	95.26	95.35	96.22	96.60	97.06	97.45	94.37	94.72	95.89
70	95.30	95.40	96.45	96.72	97.12	97.56	94.43	95.07	96.03
80	95.35	95.47	96.65	96.78	97.25	97.61	94.49	95.13	96.15
90	95.37	95.52	96.71	96.87	97.34	97.79	94.57	95.32	96.22
100	95.42	95.59	96.85	96.98	97.39	97.87	94.63	95.51	96.35

Table 2 presents the evaluation of three Machine Learning models: LSTM, FIS with FLSTM and CHAS using three key performance metrics: Precision, Accuracy, and F1-Score across different proportions of training data (10% to 100%). The performance improvements become more evident as training data increases, showing strong scalability of the models. The enhanced precision, accuracy and F1-Score of CHAS make it more suitable for early detection of arrhythmia, ensuring timely driver alerts and increased road safety.

5. CONCLUSION

This study set out to address a key gap in driver safety: the absence of continuous, real-time cardiac monitoring integrated into the driving environment. The proposed Cardiac Health Assistance System, which combines IoMT-enabled wearable sensors with a two-stage Machine Learning classification pipeline, demonstrates that it is feasible to move cardiac risk detection out of clinical settings and into the vehicle itself, without requiring drivers to alter their normal behaviour. The CHAS has outperformed over LSTM and FLSTM approaches, the findings suggest that combining classical classifiers in a staged architecture can offer a more reliable basis for on-road arrhythmia detection than single deep-learning models alone, at least under the conditions tested here. Practically, this points toward a pathway for reducing sudden cardiac events as a contributing factor in road accidents, by enabling earlier alerts to drivers, subscribed stakeholders, and healthcare providers. However, these results were obtained under simulated and offline evaluation conditions rather than live, on-road deployment, so claims about real-world safety impact should remain provisional pending field testing across diverse drivers, vehicles, and driving conditions. Similarly, while the system architecture addresses data transmission and layered processing, questions of long-term wearability, sensor robustness to motion artifacts, and patient data privacy in continuous transmission remain open and were not the focus of this evaluation.

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AUTHOR CONTRIBUTIONS

Shivashankar: Involved in concept formation, formal analysis, problem formulation, methodology, implementation, result discussion, rough manuscript preparation.

Dr. Prof. Md Shohel Sayeed: Research supervision and revision of manuscript for scientific and intellectual contented.

Dr. Andrews Samraj: Research supervision, editing and correction of manuscript.

Dr. Manjunath R: Research concept formation, performance evaluation of CHAS algorithm and result interpretation.

Dr. Sowmya Naik P T: Validation, editing, and correction of manuscript.

Prof. Surendrababu M S: Testing, correction, editing and correction of manuscript.

Dr. Manjunath C R: Software analysis**,** performance evaluation of CHAS algorithm and result interpretation, editing and correction of manuscript.

CONFLICT OF INTEREST

The authors declare that they have no known financial or non-financial conflicts of interest that could have influenced the research, its methodology, results, interpretation, or publication of this manuscript.

ETHICS STATEMENT

The study was conducted in accordance with applicable ethical guidelines, with appropriate ethical approval and informed consent obtained from all authors, while ensuring the confidentiality and privacy of their data.

DATA AVAILABILITY STATEMENT

All data supporting the results presented in the study can be obtained from the corresponding author through reasonable request. The data are not available publicly as they were generated and analysed within the scope of experimental validation of the proposed Machine Learning and CHAS based human activity monitoring system.

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