Shortwave Based Electrocardiogram Cognizanze System

[1]Hariharan R, [2]Arunkumar M, [3]Ramprakash R, [4]Hemananth, [5]Sheikameer Batcha S and [6]Mohan raj
[1,2,3,4,5,6] Department of Electrical and Electronics Engineering, Sri Eshwar college of Engineering, Coimbatore, India.
[1]hariharan.r@sece.ac.in, [2]arunkumar.m2019eee@sece.ac.in, [3]ramprakash.reee@sece.ac.in, [4]hemananth.b@sece.ac.in, [5]sheikameerbatcha.s@sece.ac.in, [6]mohanraj.c@sece.ac.in

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Abstract – Portable Electrocardiogram (ECG) video display units are wanted for aged and far-flung sufferers who cannot go to the medical institution frequently. The answer connects sufferers and docs thru a cloud IoT server that gives all of the records had to discover coronary heart disease. Using an Electrocardiogram monitoring apparatus and the MQTT protocol, the patient collects and uploads data about their current health status toward the server. The Internet of things The functionality of a cloud server additional examination that benefits both the patient and the doctor. The proposed system also includes an warning system for alerts users when a predetermined limit is breached.Real-time data collected by the monitoring system, as well as Physio Net Electrocardiogram-ID benchmark data as well as an Electrocardiogram machine The system structure consists of input, an embedded device, a cloud server for stuff on the internet and an interface. This article includes two experiments that take each Varieties of incoming information. Results suggest that the proposed system provides dependable and trustworthy results, which may reduce the number of hospital visits required. A comparison is made between the proposed system and a number of previously mentioned methods in the literature. Finally, the intended system is put into action to demonstrate how it works.

Keywords – Electrocardiogram, Internet of Things, Trustworthy, Frameworks.

I. INTRODUCTION

Notable rise in the number of patients with cardiovascular illnesses has been observed with population ageing. As a result, hospitalization, treatment, and monitoring cost more money when it comes to healthcare. This study presents an architectural framework for a system that makes use of mobile technologies to provide continuous, wireless electrocardiogram (ECG) monitoring of patients wherever they are. Any abnormal Electrocardiogram readings are recoganised by the system's intelligent agents, who then raise an alarm that, in the event of an emergency, is transmitted to the hospital. In addition to enabling patients the freedom to roam about freely and continuously monitoring their hearts, the suggested system would also lower healthcare expenses while improving the quality of life for patients.

II. DESIGN

ECG classification algorithms play a significant role in processor optimization. We present a neural network with a small footprint that combines BLSTM and CNN in this section [1]. **Fig 1** depicts an Electrocardiogram signal of a typical heartbeat. The clinical significance of P, Q, R, S, S, and T waves cannot be overstated. A typical Electrocardiogram signal of a heartbeat, complete with P, Q, R, S, and T waves.

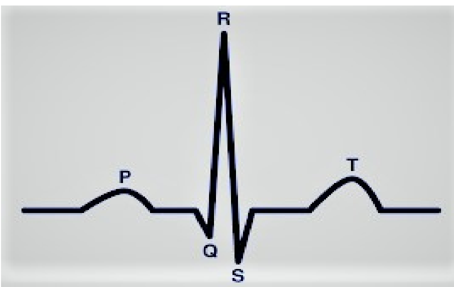

Fig 1. Wave Form.

An Electrocardiogram signal showing a typical heartbeat with important details such as the P, Q, R, S, and T waves. It represents myocardium electrical activity. The P wave represents atrial contraction, the T wave represents ventricular relaxation, and the QRS complex represents ventricular contraction [2, 3].

III. STEP-BASED ECG SIGNAL ANALYSIS USING MACHINE LEARNING AND CONVENTIONAL SIGNALPROCESSING

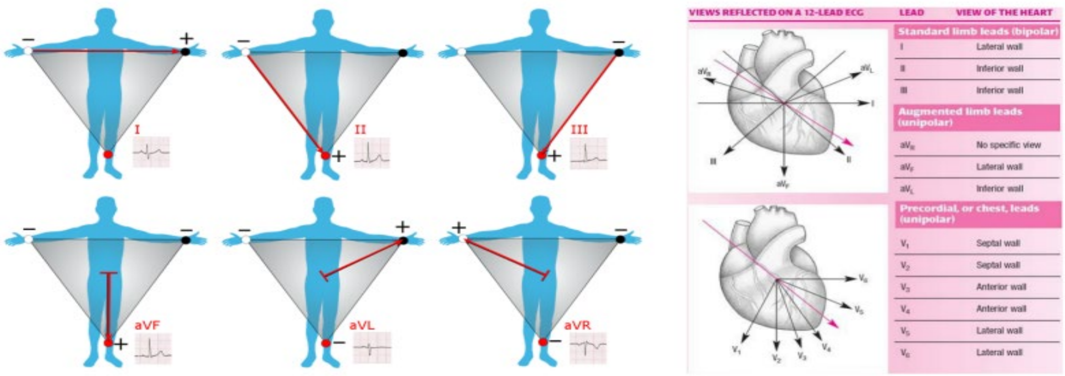

Fig 2. Traditional Signal Processing to Machine Learning Approaches.

Stage1:Source Of Data Acquisition/Dataset

The motivation is data set selection when it comes to Electrocardiogram signal analysis for feature extraction and/or beat classification based on various arrhythmias. The characteristics recorded with the Electrocardiogram aid in determining which features to extract or investigate further. Annotations, type, number of tracks, number of records used, number of patients, age, gender, and health status are all attributes that guide the remaining phases of the Electrocardiogram evaluation procedure for classification [4-7]. This phase treats different Electrocardiogram information series source as inputs to the stage-based model, but focuses on the data sources in particular. **Fig 2** shows traditional signal processing to machine learning approaches.

Stage2: Denoising

Noise is acquired along with the original signal during Electrocardiogram signal acquisition, which has a significant impact on Electrocardiogram quality and classification. A bandpass filter (0.05 to 45 Hz) with sample entropy is a traditional method for denoising Electrocardiogram signals [8-10]. Noise can take many forms, but he is primarily classified into two types. External noise and internal embedded noise Power line noise or other random noise can be considered external noise.

There are several methods for removing noisy signals. The structural similarity matrix (SSIM) can be used to check Electrocardiogram signal quality and evaluate it using Metrics such as SNR (signal to noice ratio). **Fig 3** shows stage based ecg signal analysis.

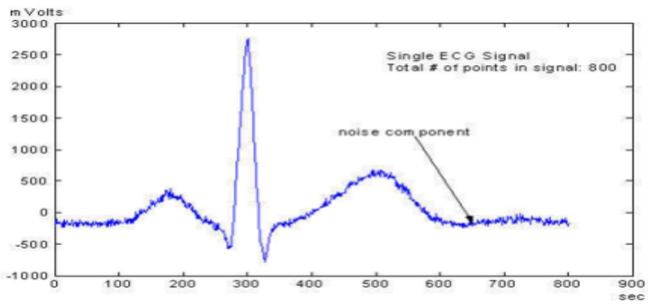

Fig 3. Stage Based ECG Signal Analysis.

Stage 3: Feature Engineering

The proper identification of waveform landmarks is required for Electrocardiogram classification. The QRS complex is the main wave of the Electrocardiogramreturned signal heart's ventricular contractile motion. Its shape serves as the foundation for automatic feature recognition and serves as the site of origin of various classification methods. However, due to the physiological variability of QRS and the presence of various sources of noise in the Electrocardiogram signal, it is difficult to detect the QRS accurately. Many conventional signal processing and ML (machine-learning) approaches to feature engineering (FE) have been proposed over the last decade to find QRS complexes, ST segments, R-peaks, and other determining factors [12-15].

Stage4: Classification

The final step of the Electrocardiogram process ofsignal evaluation, after the Electrocardiogram signal has been acquired and has traversed the noise unwanted filtering and feature development steps, uses the identified reference points to classify the Electrocardiogram signal into different classesdepending on the topical issue. is going to be In this section, we will look at both conventional and ML point of views to classifying Electrocardiogram signals that have been described in the literature [17].

Machine Learning Approaches

Artificial intelligence (AI) and machine learning are two areas of computer science that deal with computer intelligence (ML). It includes a variety of techniques that allowcomputers to recognize various ways to efficiently represent data using various algorithms [18, 19]. AI can be usedto predict or classify data using a variety of supervised and unsupervised learning goals. Unsupervised learning is concerned with revealing underlying structures, whereas supervised learning is concerned with categorizing a variety of categories, such as normal and irregular rhythms. For supervised learning, data sets with labelled or structured data are essential. Predictive modeling necessitates the use of a set of characteristics known as predictors [21].

Traditional ECG Classification Approaches

Threshold-based methods have been used to classify normal and abnormal Electrocardiogram beats. presented a modified adaptive threshold approach based on Pan-Tompkins [22]. As described in the DWT is also used to classify his Electrocardiogram using principal component analysis (PCA) and independent component analysis (ICA). When tested against the MIT-BIH arrhythmia data set, the Multimodal Decision-Learning (MDL) algorithm reached 100% awareness of classifying Electrocardiograms as usual or unusual.

IV. REAL-TIME MONITORING

Wearables and dress able battery-powered, as well as,electronic sensors may be integrated into mobile phones, smart watches, e Patches, and wearable handheld monitors. This integration allows for continuous Electrocardiogram monitoring, which improves real-time monitoring, detection, and treatment of a variety ofvascular conditions. These wearables and clothed in sensors can detect QRS complexes and other Electrocardiogram features by recording and analyzing Electrocardiogram signals [23-25]. Electrocardiogram tracking and analysing data performed in 3 ways. These are referred to as three distinct systems in this document.**Fig 4** shows real-time monitoring.

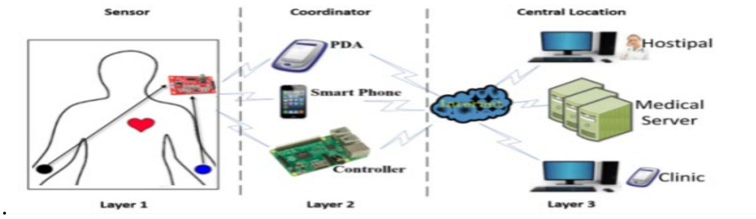

Fig 4. Real Time Monitoring.

V. ECG BIOSCRYPT

Acquisition, filtering, segmentation, feature extraction, and adaptation are the five main components of Electrocardiogram-based biometric systems [26].

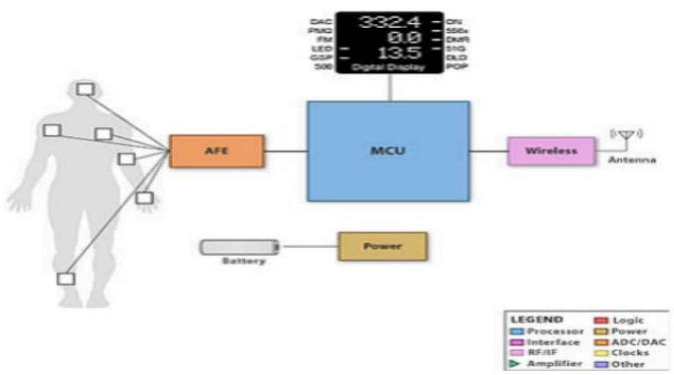

Fig 5. ECG Bioscrypt.

Fig 5 depicts the overall structure and flow of the Electrocardiogram-based biometric authentication process, which includes enrollment and an overview of the biometric electrocardiogram authentication system. Filtering, segmentation, function extraction, templates, and matching modules are included. The user's girlfriend's Electrocardiogram alerts are enrolled in the enrollment phase to generate a template. During the authentication phase, the user's raw data is supplied and compared to previously saved templates to determine access privileges. Below, we describe a method for implementing an Electrocardiogram -primarily based completely biometric algorithm, as well as the various steps of the authentication algorithm.

VI. PRE-PROCESSING

To distinguish the desired biometric feature from the surrounding noise, pre-goal processing is used. Both low-frequency and high-frequency sound components are merged in the context of Electrocardiogram and are designated as baseline drift and powerline interference is what it is. muscle relics and outer interference can be found in high frequency noise. Electromyograms (EMGs) are produced by electrical activity in the muscles and appear as continuous fluctuations that are much speeder than Electrocardiogram waves [29]. By utilising low-pass filters, high-frequency noise is eliminated from the electrocardiogram. A high pass filter can be used to eliminate low-frequency elements such baseline wander noise, respiratory fluctuation, and motion distortions. During the preliminary processing stage, electrocardiogram info's are filtered to remove any sound that can tamper with the bio-metric alarm.

VII. DYNAMIC TIME WARPING (DTW)

DTW set side by side 2 patterns that don't have to be the similar length. The Dynamic-time-warping algorithm determines the best position between 2 patterns of changing distance, such that the total of the positional distinctions between each pair points is as tiny as viable. This algorithm seems to be able to handle comparisons. between templates, queries, even Should they not be positioned, as in handprints, or if they differ in length, as in ECGs. This study demonstrates the Respiration Rate (RR) separation method based on variability. Briefly, each RR segment is unique. As a result, DTW is important. The DTW measures the same things betweenECG feature sets are aligned, then analysed using a template.**Table 1** shows the comparison table.

Table 1. Comparison Table

Reference	**Proposition**	**Location**	**Memory**		**Data transfer**	**Web application**	**Multiple patient**	**Battery**	**Emergency request**	**Medical history**	**Battery change request**
			Local	**Server**							
[11]	Portable ECG monitoring system design	Chest	Yes	Yes	Wi-Fi	Yes	No	N/A	No	No	No
[20]	Wireless ECG monitoring system for telemedicine application	On body	Yes	Yes	UART	Yes	Yes	N/A	No	No	No
[28]	IOT based portable ECG monitoring system for smart health care	Chest	N/A	Yes	IOT	Yes	Yes	Yes	Yes	Yes	No
[27]	Continuous ECG monitoring with low power electronics and energy harvesting	ARM	N/A	Yes	Wi-Fi	Yes	No	Yes	No	No	No
[16]	Remote health care system	Singlet	Yes	Yes	BLE	Yes	Yes	Yes	Yes	Yes	No
proposed	Shortwave based electrocardiogram cognizance system	On body	Yes	Yes	IOT	Yes	Yes	Yes	Yes	yes	Yes

VIII. ALGORITHMS WITH BEST PERFORMANCE

The 1st round chart displays information about ML (machine-learning) methods, such as the total % of neural network methods. The data in the 2nd round chart depicts the distribution of the best performing neural connection methods. The graph's relative percentages show that neural networks outperformed other algorithms in 28% of studies. This 28% is issued across various types of inter connection methods, as shown in the second pie chart. Convolutional neural networks outperformed the other networks with a relative probability of 6%, according to the second pie chart, from there on unnatural interconnected procedures or flat interconnected systems.Multi-layer perceptron, deep interconnected systems, and LSTM (long short-term memory) each perform well 3% of the time, while the other algorithms, such as ResNet, far down belief networks, GRU, VGG, and ensemble Artificial Intelligence, perform 2% of the time. The performance was evident in this case. As a result, we can conclude that, when compared to ResNet and VGG, CNN outperformed them in the majority of cases, particularly when used for image classification applications. For multiparameter inputs, time and frequency-domain functions, procedures such as multi-layer perceptron, far down interconnected systems, and ANNs have demonstrated excellent performance. In addition, there are algorithms that have demonstrated superior performance in specific applications. AI ensemble, LSTM. The 1st round chart in the pic below that appear the help vector machine performed well in 27% of the statistics, while the random forest algorithm performed well in 19% of cases. Because most sensor features are time- and frequency-domain features, multitype property vectors, or numerical property vectors, SVMs and random forests are superior for most studies. In 6% of research, selection trees and ensemble studying performed good, However, the boosting method worked well in his 5% study as well.**Fig 6** shows the algorithms with best performance.

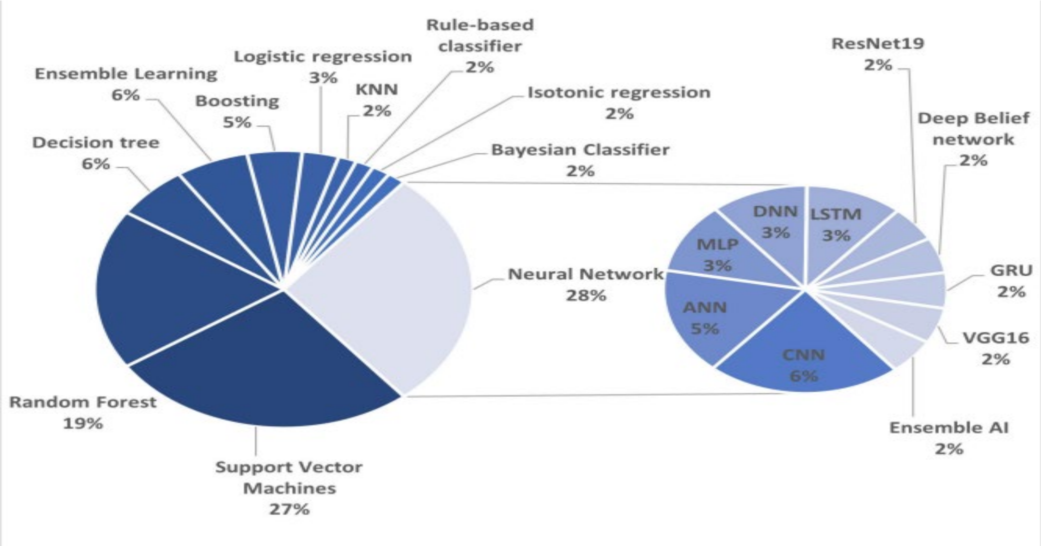

Fig 6. Algorithms with Best Performance.

Regression, Bayesian classifiers, and ANN performed well in less than 4% of the studies. We can conclude that it performed satisfactorily.

IX. CONCLUSION

This study introduces a new IOT your assisted electrocardiogram monitoring system, which is intended primarily for heart health monitoring applications. To summarize, the ECG monitoring system assesses thepatient's state of health. The contact-less ECG observing system eliminates the need for direct skin contact and allows for comfortable long-term monitoring. This proposed system has the potential to significantly reduce hospital congestion while also monitoring for heart problems remotely. As part of this research's future work, additional sensors will be added to propose a system for measuring temperature, user movement, and the TE used to detect EEG or EMG.

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