Deep Neural Network Based LSTM and Hybrid CNN

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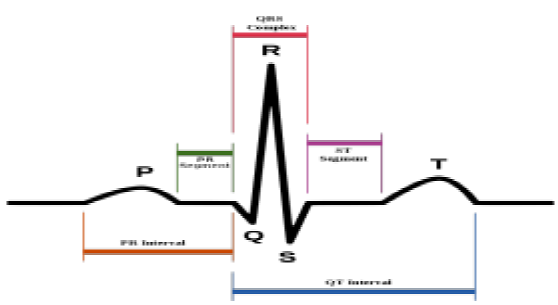
ABSTRACT

When the heart pumps, oxygen-rich blood travels via coronary arteries to the organ. Coronary artery disease is a result of atherosclerosis (CAD). Hemorrhagic atherosclerosis is a term used to describe plaque buildup in the arteries. Early non-invasive screening for a wide range of life-threatening cardiovascular illnesses is now possible thanks to the latest advancement in artificial intelligence. When these techniques have been used, there have been fewer CAD diagnoses.' Two non-specific indicators of coronary artery disease (CAD) have been used in this study to develop an effective approach for incorporating them (HRV). Using a Convolutional Neural Network (CNN), morphological ECG features can be extracted. To get a better idea of HRV, you can use an approach that combines the advantages of both LSTM and a host of custom statistical factors. As a consequence, a hybrid CNN-LSTM architecture is used to categorize CAD using the two biomarkers.Both the MIMIC II waveform data and an in-house noisy ECG sensor dataset are used to evaluate the proposed method's viability in real-world situations. Classification accuracy on the two datasets was 93% and 88%, which was better than the prior approaches.

“Keywords: Coronary Artery Disease (CAD), ECG, CNN, LSTM, Hybrid Architecture

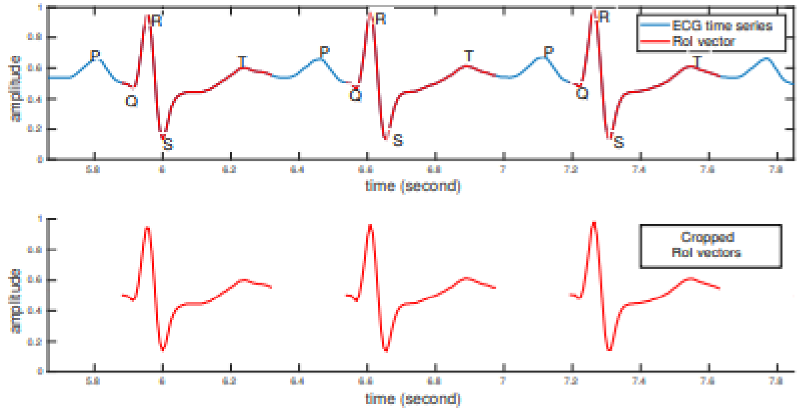
I.INTRODUCTION”

When cholesterol and other fats build up inside the coronary artery's inner walls, it results in cardiovascular disease (CAD). An embolism or cardiac arrest may arise from the restriction of blood flow via the coronary vessels as a result. The gold standard diagnosis for CAD, coronary angiography, needs an overnight hospital stay[1-5]. Many life-threatening cardiovascular illnesses (CVDs) can be prevented by early identification. Due to a worldwide shortage of doctors and patients, artificial intelligence-based screening approaches are becoming increasingly popular in both emerging and developed countries. Low-cost, non-intrusive, and clinician-involved screening technologies are needed. There is still no non-invasive way to diagnose CAD. In the early stages of the disease, CAD is frequently asymptomatic, however studies have found a number of non-specific biomarkers for the condition. An key surrogate sign for HRV (Heart Rate Variability) is largely accepted



“Figure:1.1Components of a normal ECG cycle. Source [11,12]

It is important to remember that the ECG cycle has three main components [15]. Atrial depolarization is represented by P waves; QRS complex is represented by the ventricle depolarization; whereas T wave is represented by ventricle repolarization. AV node to the sinus node, the PR interval measures how long it takes for an electrical impulse to travel between these two points in time. The ST segment measures the time it takes for the ventricles to depolarize and repolarize[11,12]. In order to calculate the heart rate, the distance between R peaks must be taken into account.



"Figure: 1.2A sample ECG signal, indicating the RoI vectors[10]

1.1 CONTRIBUTIONS OF THE PAPER

- An ECG morphological feature extraction structure based on a Convolutional Neural Network (CNN).
- An LSTM network and custom attributes are used to create a bespoke HRV vector.
- For the first time, an illness classification architecture that incorporates both CAD markers into one system is being developed.
- A method for selecting relevant handcrafted features linked to HRV using an algorithm.
- An algorithm for extracting time series from commercially available low-cost ECG sensors that produces clinically interpretable digital ECG pictures.

2.LITERATURE SURVEY

An ECG (electrocardiogram) is a device that monitors the electrical activity of the heart.An easy and painless way to check for heart problems and keep tabs on your cardiovascular health. Analysing the ECG data was a consideration. We randomly chose 80 percent of the selected corpus to be used for training and 20 percent to be used for testing. To ensure that the HRV can be accurately measured, recordings are limited to a maximum of two minutes in length. Each topic had a total of 100 non-overlapping examples picked.

C.Venkatesan et al. (2017) [1] advocated the use of SVM-based arrhythmic beat classifications and ECG signal pre-processing to distinguish between healthy and abnormal people. The pre-processed data is subjected to a discrete wavelet transform for the extraction of HRV features, and machine learning methods are employed to classify arrhythmic beats. To classify a beat, an SVM or other common classifier is employed to reduce background noise. SVM classifier outperforms all other machine learning-based classifiers, as shown by the final Results section.

HariMohan et al. (2020) [2] In order to accurately and automatically detect cardiac arrhythmias, a hybrid CNN-LSTM deep learning model was developed. The model's performance is validated using data from the MIT-BIH arrhythmias database and the PTB diagnostic database. The suggested model's input is the ECG beat time interval. With the most up-to-date assessment approach. The suggested model has an accuracy rate of 99 percent on average and 99.7 percent on average.

Khairul et al. (2014) [3] For ECG samples with abnormal cardiac conditions, we created an effective biometric extraction strategy that helped improve the identifying process for the person. The stability of the system was tested using QRS complexes. An impressive 96.7 percent accuracy for MITDB, 96.4 percent for SVDB, and 99.3 percent for DiSciRi were achieved in this studyLow-frequency ECG recordings and a larger number of ECG samples are used in the suggested strategy to enhance classification performance.

Mohamed et al. (2020) [4] A heart disease prediction system was created using the LSTM method. In the study of heart disease, LSTM and MLP approaches are being tested for accuracy and other predictive properties. Preventing and monitoring heart disease and stroke will be a significant goal of the LSTM-based intelligent system that is being developed for this project. When it comes to solving these problems, adopting LSTM instead of MLP has proven to be the most effective.

Mohammad Ayoub khan (2020) [5] presents a Modified Deep Convolutional Neural Network IoT platform for assessing heart disease more accurately (MDCNN).The patient wears a smart watch and an electrocardiogram (ECG) monitor to keep track of their blood pressure and heart rate (ECG). According to the findings, the suggested MDCNN-based heart disease prediction system outperforms other techniques. In comparison to other classifiers, the MDCNN has a higher accuracy rate of 98.2 percent, as shown by the suggested approach.

SenthilKumar et al. (2019) [6] The suggested approach uses machine learning methods to identify important traits. Cardiovascular illness may be predicted more accurately as a consequence of this Various combinations of characteristics and recognized categorization methods are used in the model's creation. increased performance with an 88.7 percent accuracy level with the use of the hybrid random forest with a linear model to predict cardiac illness (HRFLM)

Sumeet et al. (2012) [7] When studying the HRV signals, nonlinear properties such as entropy, Shannon entropy, and approximation entropy, as well as sample entropy, were gleaned using recurrence plots, Poincare plots, and detrended fluctuations analysis (DFA) (SampEn).Principal component analysis is used to analyse this process (PCA). These methods were put through their paces in order to discover which one provided the most accurate classification of patients into the normal and CAD categories. Using our suggested strategy, the multilayer perceptron method (MLP) achieved a classification accuracy of 89.5%.

Tamanna et al.(2019) [8] presented a new ECG monitoring system based on Internet of Things technology (IoT). Patients' electrocardiogram (ECG) signals are gathered by wearable sensors and monitored often by the system, which stores the data in a database that is only accessible to authorized employees. An email is automatically sent to the users and physicians if any malformations are discovered. This low-cost IoT gadget has the potential to lower the number of people who become disabled or die as a result of cardiovascular disease.

UttamDeshpandeet al.(2017) [9] Cypress's WICED (Wireless Internet Connectivity for Embedded Devices) (IoT). Wireless transmission is used by portable ECG monitoring devices to deliver data to the Internet of Things (IoT) cloud. Protocols like CoAP/HTTP and MQTT, TLS/TCP, and OMALWM2M are used in the Internet of Things to send data.

Yuepenget al.(2020) [10] Assembled an algorithm to predict cardiac illness using random forests and long-term memory neural networks (LSTM). After LSTM, KNN, and DNN calculations were conducted to determine whether the accuracy of the prediction increased after screening, the most reliable calculation was picked to construct the cardiac sickness forecast model.

2.1 IMPLICATIONS ON LITERATURE SURVEY

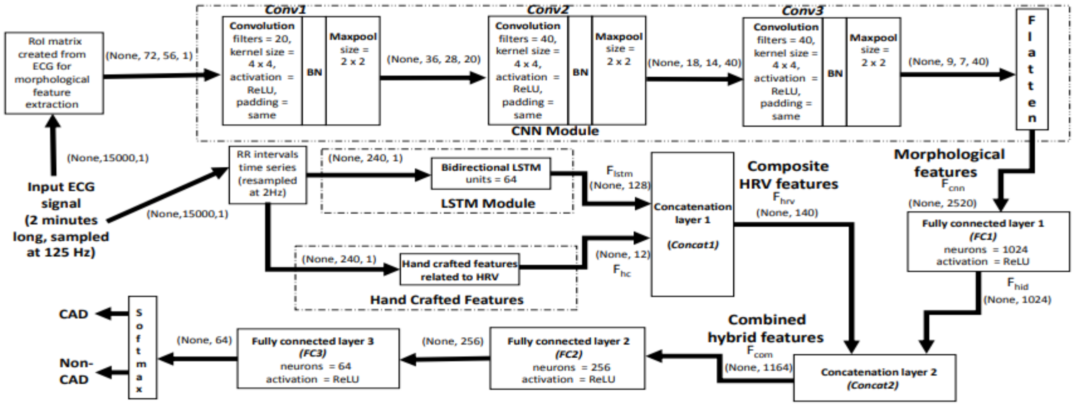
HRV seems to be the CAD method of choice for the bulk of current AI approaches, according to a literature review. Using a deep architecture to automatically extract relevant information from raw signals, deep learning applications in biomedical engineering have lately gained prominence. Arrhythmias and atrial fibrillation may be detected using these approaches when the biomarkers are well-known and conspicuous in the input. CAD has yet to have a clear biomarker that has been clinically verified [13,14]. For our work in the medical area, we have created a deep learning approach for merging two nonspecific surrogate CAD symptoms, abnormal ECG morphology and irregular heart rate variability. For example, both markers have a high level of sensitivity and are very specific. An improved screening system accuracy results.

3.PROPOSED SYSTEM

The goal is to create an LSTM-CNN hybrid neural network by combining nonspecific indications of coronary heart disease with abnormal ECG patterns. It includes a CNN module for ECG, an LST model, and an algorithmic feature set that may be used to analyse ECG morphological features. To map the CNN feature, a composite HRV vector is created by combining the LSTM output with hand-crafted features. A single classification goal is the focus of the hybrid network, which is fine-tuned throughout.

3.1 ARCHITECTURE

- Method for efficiently extracting morphological features from an ECG with Convolutionary Neural Networks
- The combination of an LSTM network with hand-crafted features results in an HRV vector that is both efficient and accurate.



"Figure: 3.1 Proposed hybrid CNN-LSTM neural network architecture for classification of CAD"

- Two distinct CAD markers may be combined into a single disease classification structure by use of a CNN-LSTM hybrid structure and hand-crafted features.
- HRV-relevant handcrafted characteristics are selected using an algorithm that uses an algorithm.
- Process for extracting therapeutically relevant time series from clinically interpretable digital ECG pictures using low-cost, commercially accessible sensors.

Mutual information for each pair of data is supplied by I, which is mutual information for the grid G for each pair of data (xy) lower than B(n) given by

$$MIC(D) = max_{xy<B(n)}\{M(D)_{x,y}\} \quad (1)$$

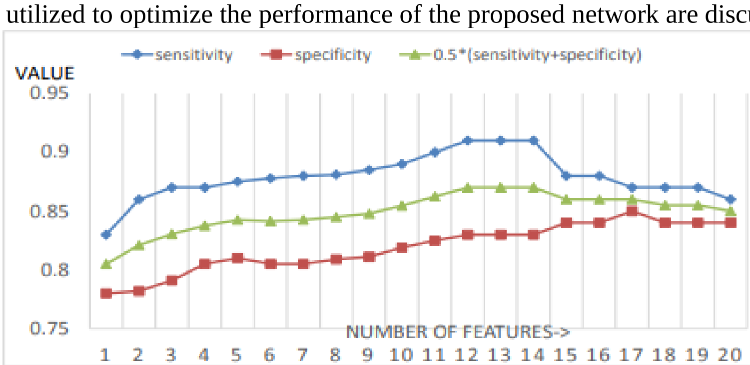
n is the sample size, and B(n) is a function of this sample size. M(D) varies depending on the distribution of G Eqn. (1).

$$M(D)_{x,y} = \frac{max\{I(D|G)\}}{\log min(x,y)} \quad (2)$$

High MIC suggests a trait that should be taken into consideration Eqn. (2). Use of subject level 5-crease cross-approval is used to choose a suitable collection of capabilities from the positioned inclusion list based on normal order execution on comparable prepared datasets

4.RESULT AND DISCUSSION

The suggested technique is tested on a variety of patient demographics, sensor devices, and overall signal quality datasets. The waveform data was taken from the MIMIC II waveform collection and consists of CAD and non-cardiac individuals. Our suggested technique for selecting appropriate hand-crafted HRV characteristics and other hyper-parameters utilized to optimize the performance of the proposed network are discussed in this part.



"Fig: 4.1Average subject level 5 fold cross validation performance on MIMIC II training data."

Network Structure	*Training* set		Test set $D1$		Test set $D2$	
	Se	Sp	Se	Sp	Se	Sp
CNN (for ECG morphology)	0.83 ± 0.03	0.94 ± 0.04	0.82	0.94	0.78	0.89
Bi-LSTM (for HRV)	0.94 ± 0.04	0.80 ± 0.06	0.93	0.78	0.90	0.77
Hand crafted features (for HRV)	0.91 ± 0.05	0.83 ± 0.02	0.90	0.82	0.86	0.80
Bi-LSTM + hand crafted features (for HRV)	0.96 ± 0.05	0.85 ± 0.03	0.95	0.83	0.92	0.81
CNN + Bi-LSTM + hand crafted features (ECG morphology + HRV) (proposed hybrid CNN-LSTM)	**0.94 ± 0.04**	**0.93 ± 0.03**	**0.94**	**0.92**	**0.90**	**0.85**

Table I: Performance comparison of the proposed hybrid CNN-LSTM network

Prior art	Test set $D1$		Test set $D2$	
	Se	Sp	Se	Sp
Dua *et al.* [5] (classical machine learning)	0.80	0.75	0.77	0.71
Acharya *et al.* [7] (classical machine learning)	0.88	0.83	0.82	0.78
Baseline 1D CNN (deep learning)	0.73	0.90	0.71	0.85
Proposed approach (hybrid CNN-LSTM)	**0.94**	**0.92**	**0.90**	**0.85**

Table II: Performance comparison with existing approaches

5.CONCLUSION AND FUTURE WORK

A key field of medical study is low-cost, non-invasive CAD screening. Using a CNN-LSTM approach, we have developed a superior screening system that incorporates two unique non-specific CAD markers into a single hybrid design. One of the datasets was collected in a more realistic context using low-cost sensors, and it was assessed on both of those datasets.Using this method, only a small percentage of patients are missed as being at risk. A person's demographics, lifestyle, and family medical history all have an indirect impact on a person's risk for coronary artery disease (CAD).

FUTURE WORK

Integration with a real-world maintenance scheduling tool in an industrial setting, testing the proposed technique in diverse industrial equipment to evaluate its applicability and components of cyber security inquiry will be included to the proposed energy analysis technique in the future.

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BIOGRAPHIES

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