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*Original Article*

# Advanced ECG Signal Classification Using Deep Learning Networks for Early Disease Diagnosis in Healthcare

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***Abstract*** *- Healthcare is producing vast amounts of data, providing new opportunities for early disease detection and improved patient care. Electrocardiograms (ECGs) are widely used to identify cardiac abnormalities; however, manual interpretation is often time-consuming and prone to inaccuracy. This study proposes an advanced deep learning framework for automated ECG signal classification, enabling precise and rapid identification of cardiac disorders. The approach involves careful data preprocessing noise elimination, augmentation, normalization, and feature extraction followed by training a Recurrent Neural Network (RNN) to capture the time-dependent dynamics of sequential ECG data. Model performance is evaluated using accuracy, precision, recall, F1-score, and ROC metrics. The RNN model is compared against baseline models such as Convolutional Neural Networks (CNN), Random Forest (RF), and ResNet50. Results show that while CNN achieved 49% accuracy, RF reached 83.7%, and ResNet50 achieved 94.02%, the proposed RNN attained superior performance with 99.5% accuracy, 99.4% precision, 99.2% recall, and a 99.2% F1-score. These results highlight the RNN's effectiveness in detecting subtle cardiac irregularities. The proposed framework significantly reduces human error, accelerates clinical decision-making, and enhances patient outcomes, demonstrating strong potential for real-world healthcare applications and early disease diagnosis.*

***Keywords*** *- ECG Signal, Smart Health System, Disease Prediction, Electrocardiograms, Signal Image Processing, ECG Dataset.*

## 1. Introduction

The healthcare industry is undergoing a revolution and with it the massive potential, and the immense challenge of handling the enormous medical information. Electronic medical records (EMRs), medical imaging, genetic data, and clinical records contribute to the massive volumes of data produced by the healthcare business[1]. Heart disease, diabetes and CKD are long-term diseases that exist in the world and cause deaths to millions of people annually [2][3]. They are also insidious and may be asymptomatic for a long period of time, which makes them difficult to diagnose at the right time. The individual might experience severe complications, high cost of medical treatment, and low quality of life because of the long process of diagnosis and treatment. With the world assuming the forefront in the fight against the growing burden of chronic diseases, there is a need to have effective and early diagnostic tools **for** early intervention and outcome on the patients [4][5].

Early and accurate detection of heart issues is crucial in averting severe outcomes as well as enhancing patient outcomes. The conventional method of diagnosing heart illnesses has been based on imaging, patient history, clinical examinations, and interpretation of electrocardiogram (ECG) signals. cited in [6][7][8]. ECG signals are quite significant in diagnosing numerous heart diseases due to their ability to give real-time data about the electrical activity of the heart. The heart diseases that may include Myocardial infarctions, arrhythmias, cardiac irregularities and ischemia are usually identified using electrocardiogram (ECG) signals. Conversely, manual interpretation of ECG signal may prove to be tedious, inaccurate and hard to process with large-scale screens or where anomalies are minor in nature [9][10][11]. Integration of higher-order analytics, artificial intelligence (AI), and machine learning (ML) and deep learning (dL) can result in enhancing patient outcomes, simplifying clinical processes, and redefining healthcare systems in order to offer improved care and improved health outcomes among the population.

This has ushered us into a new era of predictive potential of early disease detection with the help of ML. Among the benefits of ML in early disease detection, it is possible to mention the fact that it is capable of processing an enormous number of variables at the same time. With the case of ML 6 algorithms, the amount of inputs that they can be fed is much more extensive than the conventional ones, which can possibly assume a small number of diverse symptoms, considering the genetics, family history, and other human behaviors and environmental circumstances [12][13][14]. The benefit of the method is that one can measure the risk of sickness with a greater degree of accuracy and specificity for the patient. It has been discovered that ML methods can be used in numerous fields of medicine. As a single more recent example, in radiology, the more sophisticated imaging tools like CT and MRI produce tens of millions of pixels of information that surpass the capacity of the human radiologist to access the information whole. DL and AI are emerging tools that have just been developed as powerful healthcare tools. DL algorithms that can be used to recreate the human brain and capabilities such as pattern recognition have been used in multiple medical environments [15], such as image recognition or predictive modeling [16][17][18]. With big data, fine patterns in medical records can be identified using these models that a human doctor can ignore these patterns. The potential of this capacity in the early diagnosis of diseases is enormous particularly in chronic diseases where early intervention is relevant.

### *1.1. Motivation and Contribution*

One of the most popular, inexpensive, and non-invasive ways to diagnose heart problems is using an electrocardiogram (ECG). However, human interpretation of these images is laborious, prone to mistakes, and may miss intricate or subtle patterns. Automated and intelligent diagnostic technologies that can increase ACC and efficiency in clinical practice are urgently needed due to the increasing frequency of cardiovascular illnesses. DL techniques, with their proven ability to extract high-level features and recognize intricate patterns in biomedical signals, present a powerful opportunity to enhance ECG signal classification. Utilizing these capabilities can facilitate the earlier detection of diseases, reduce diagnostic delays, and facilitate timely medical interventions, thereby enhancing healthcare delivery and improving patient outcomes. This research offers several key contributions as listed below:

- Developed an advanced Recurrent Neural Network (RNN) framework for ECG signal classification, capable of capturing sequential dependencies and temporal patterns for accurate disease diagnosis.
- Better signal quality and guaranteed reliable model training through the application of a comprehensive preprocessing pipeline, which comprised noise removal, data augmentation, and normalization.
- Conducted a comparative analysis of performance with the previous models (CNN, RF, ResNet50) and demonstrated the high ACC, PRE, REC and F1 of the suggested RNN.
- Stratified sampling, ROC/AUC assessment, loss-ACC curve analysis provided the validity of the model, which was found effective in early detection of the disease in a healthcare facility.

### *1.2. Novelty and Justification*

The paper presents a scheme of ECG signal classification with the help of DL that dwells on time-related characteristics of cardiac activity; it is not based on the conventional scheme of using manual feature extraction. The method uses the fact that complex neural networks can trace the occurrence of small and delicate changes in the ECG patterns that would otherwise have been ignored in the conventional analysis. The approach combines the preprocessing techniques with the consideration of the development of an efficient and automatic diagnostic model, grounded on systematized preprocessing and feature enhancement and progressive modeling. The paper is justified as to date no more significant area of research than cardiology, where the instruments of automated diagnostic would be of utmost importance in the minimization of the human error, the process of clinical decision-making and the enhancement of patient outcomes. Furthermore, the methods can also be applied to the larger healthcare work in favor of predictive and preventive medicine.

### *1.3. Organization of the Paper*

The paper is organized in the following manner: Section II is a survey of the research on expanding electrocardiogram (ECG)-based medical diagnosis of illness. Section III details the dataset, preprocessing steps, and model implementation; Section IV displays experimental results with comparison analysis; and Section V summarizes important findings and suggests directions for future research.

## 2. Literature Review

The production of this study was guided and strengthened by a comprehensive evaluation and analysis of important research studies on healthcare disease diagnostics.

Ding et al. (2025) offer a practical way to classify and detect cardiovascular issues using ECG data, with an emphasis on improving ACC through the use of DL, CNN and LSTM techniques. With ECG signals, the suggested LSTM model achieved 98.6% ACC in user authentication and 99.5% ACC in heart illness categorization. These results show that classical machine learning and convolutional neural network models are less efficient [19].

Subbarayudu et al., (2025) implemented in this study to improve disease- prediction and categorization. The BiLSTM efficiently captures sequential dependencies in patient data, increasing predictive accuracy, while the component extracts high-level abstract characteristics. The R2 Score, MAE, and RMSE are the three main regression metrics used to assess a prediction model's efficacy in this research. A poor fit and lower performance than a simple mean-based predictor were indicated by the model's R2 score of -8.905 [20].

T, P and S, (2024) focus on training ML models to analyze ECG signals and classify heartbeats into categories that reflect various cardiac conditions. A database of over 20,000 ECG recordings covers a broad spectrum of normal and abnormal heart rhythms, providing a solid basis for training the model. With an impressive 97% ACC, the DT classifier proves it can identify even the most minute patterns in electrocardiogram data [21].

Khan *et al.*, (2023) the suggested system makes use of a ResNet model, which is a 1-dimensional convolutional DNN, to extract features from the input heartbeats. This technique, SMOTE, is very effective in classifying the five classifications of heartbeats in the test data along with the class-imbalance problem in the training data. The cross-validation (CV) is performed tenfold to determine the performance of the classifier based on the use of the ACC, PRE, sensitivity, F1 and the kappa. took a sensitivity of 92.41, specificity of 99.06, an average ACC of 98.63 and 92.86 PRE. The Kappa was 95.5 and the average F1 was 92.63%. The proposed ResNet outperforms other 1-D CNNs with the deep layers, as per the research [22].

Golande and Pavankumar, (2023) proposed model is composed of three processes, namely, categorization, pre-processing, and hybrid feature engineering. Pre-processing an ECG is an attempt to remove the powerline interference and the baseline without inducing any interference with the heartbeat. Using the attributes, which are based on CNNs and traditional ECG beats extraction algorithm, and construct an efficient and effective hybrid data classification strategy. The LSTM DL classifier is fed the hybrid feature vector in a sequential fashion to forecast the occurrence of cardiac illness. According to the results of the simulation, the suggested model will significantly decrease both diagnostic errors and the time required to make each diagnostic error as opposed to the methods used nowadays [23].

Śmigiel, Pałczyński and Ledziński, (2021) Identifying the optimal combination of signal information for classification purposes is the primary goal of this study. The data that was reviewed encompassed the following: the original ECG signal, features derived from the signal's entropy, QRS complexes that had been extracted, and features derived from the complexes that had been extracted, all of which were examined. A total of twenty different types of cardiac disorders were used as the basis for the examinations. The information gathered was from a PTB-XL database. Presented here is a novel approach to QRS complex extraction that uses the k-mean method to simultaneously aggregate data from well-established algorithms for multi-lead signals. What this means is that the raw signal benefits from having entropy-based characteristics and extracted QRS complexes added to it. Signals that were entropy-based but did not have QRS complexes removed fared far worse [24].

Table 1 presents a summary of recent research on disease diagnosis in healthcare, highlighting the proposed models, datasets used, key findings, and identified challenges.

**Table 1: Recent Studies on Disease Diagnosis in Healthcare Using Deep Learning**

| Author | Proposed Work | Results | Key Findings | Limitations & Future Work |
|---|---|---|---|---|
| [19] | ECG signal dataset (not specified in summary) | 99.5% ACC (disease classification), 98.6% ACC (user authentication) | CNN + LSTM model enhances classification and authentication performance compared to traditional ML and CNN-only methods | Testing on bigger and more varied datasets is probably necessary; didn't address real-time deployment and scalability. |
| [20] | Patient biomedical data (details not specified) | $R^2$ = -8.905, MAE and RMSE values indicate poor model performance | BiLSTM captures sequential dependencies; hybrid model attempted for disease prediction | Poor fit suggests data-model mismatch; future work should refine feature engineering and improve dataset quality |
| [21] | ~20,000 ECG recordings with diverse rhythms | Decision Tree achieved 97% ACC | Demonstrates ML's ability to detect subtle patterns in large ECG datasets | May lack generalizability across populations; limited comparison with deep learning methods |
| [22] | ECG heartbeats dataset (imbalanced, processed with SMOTE) | Avg. ACC: 98.63%, PRE: 92.86%, Sensitivity: 92.41%, Specificity: 99.06%, F1: 92.63%, Kappa: 95.5% | 1-D ResNet with SMOTE handles imbalance well and outperforms standard 1-D CNNs | Needs validation on real-world noisy ECG signals; computational efficiency not discussed |
| [23] | ECG dataset (not specified) | Improved ACC and reduced diagnostic errors vs. existing methods | Hybrid feature extraction (conventional + CNN) with LSTM classifier enhances prediction | Requires testing on multi-center datasets; real-time diagnostic integration to be explored |
| [24] | PTB-XL ECG database | Adding entropy-based + QRS features improved classification across 2, 5, and 20 disease classes | Demonstrated benefit of combining raw ECG with entropy and QRS features | Needs exploration with deep learning integration; performance on real-time signals not evaluated |

## 3. Research Methodology

The research procedure of the given study is organized in chronological order, where it is necessary to first collect data by using the ECG dataset. Preprocessing was applied to process missing values, elimination of duplicates, noise, increase data, and min-max normalization. The dimensional reduction method was carried out by using feature extraction in order to retain significant details. This data was represented into two categories namely training and testing, and a RNN model was developed. Key performance metrics were used to evaluate the model such as ACC, PRE, REC, F1 and ROC analysis. Fig. 1 shows the suggested flow-chart of Disease Diagnosis in Healthcare Using Deep Learning.

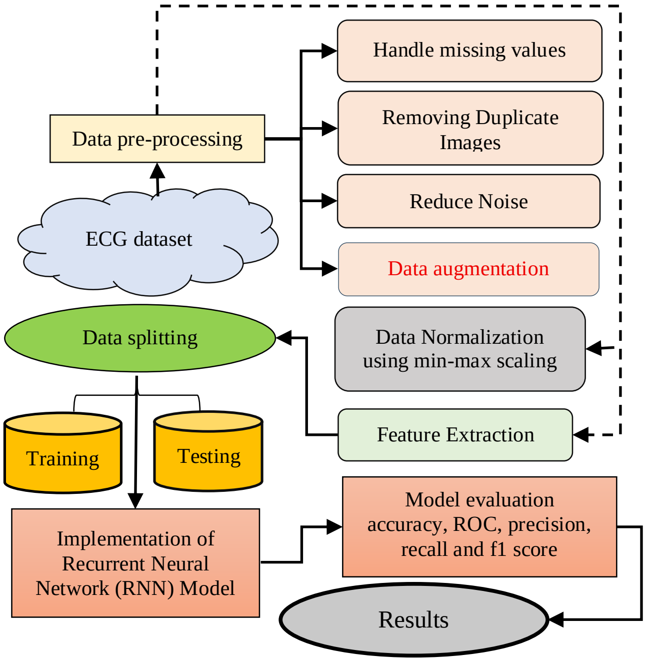


**Fig 1: Proposed Flowchart for Disease Diagnosis in Healthcare using Deep Learning**

Each step of the proposed methodology is detailed in the section that follows:

### *3.1. Data Gathering and Analysis*

The ECG dataset is used in this research. Patients' electrocardiogram readings make up the ECG dataset. In this table, each row represents a patient's full electrocardiogram (ECG). The electrocardiogram (ECG) records 140 different values simultaneously. Each patient's data is located in columns 0–139. The category categorization system of the dataset uses the numbers '0,' for normal electrocardiograms, and '1,' for problematic ones.' Data visualizations were used to examine Disease Diagnosis in Healthcare distribution, feature correlations etc., are given below:

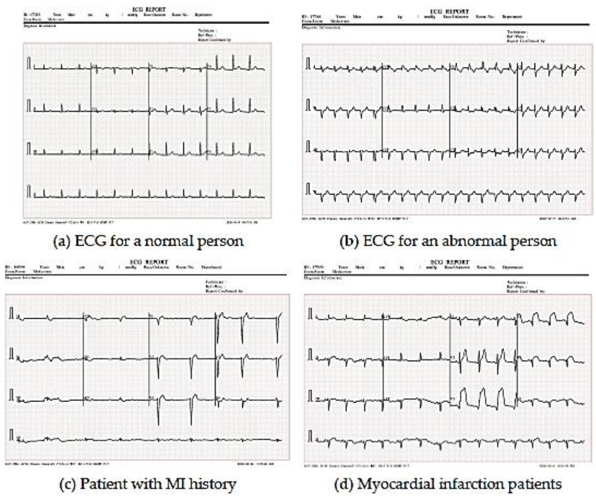


**Fig 2: Samples of ECG Dataset Categories**

Fig. 2 illustrates different ECG signal patterns corresponding to various health conditions. Subfigure (a) shows a normal ECG with regular waveforms, indicating healthy cardiac activity. Subfigure (b) presents the ECG of an abnormal person, where irregularities in rhythm and waveform deviations can be observed. Subfigure (c) displays the ECG of a patient with a history of myocardial infarction (MI), showing distinct abnormalities suggestive of past cardiac damage. Lastly, the subfigure (d) represents the ECG of a patient with an ongoing myocardial infarction, which has severe distortions and irregularities in its waveform, indicating that the patient has a severe dysfunction of the heart. Collectively, these ECG plots indicate the changes in the activity of the heart under normal, abnormal, and myocardial infarction conditions.

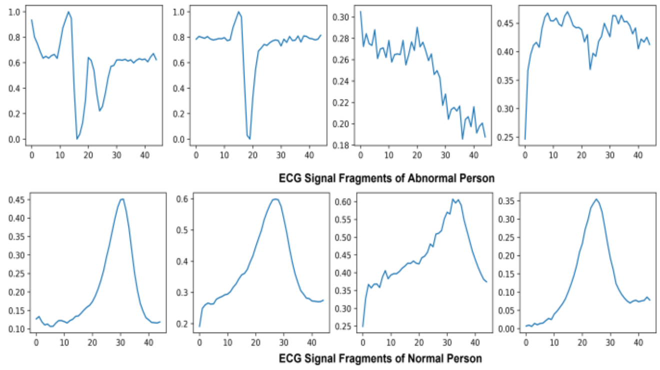


**Fig 3: Visualization of Abnormal and Normal ECG Signals**

Figure 3 illustrates pieces of ECG signals of abnormal and normal persons. The upper row depicts ECG signal fragments of an abnormal individual, in which the waveforms are irregular, exhibiting sudden changes in amplitude and rhythm and irregular fluctuations in amplitude and rhythm. Conversely, the lowest row shows ECG segments of a healthy individual, which are smooth, clearly defined peaks, with regular waveforms, which is an indication of good and constant heart activity. The present comparison reveals the clear differences in the morphology of signal in normal and abnormal ECG patterns that can be utilized to provide precise diagnosis of the disease.

### *3.2. Data Pre-processing*

The ECG data was concatenated, cleansed, and engineered. The preprocessing methods involved: processing of the missing values, elimination of duplicated images, noise reduction, data augmentation, and normalization. The major steps involved in preprocessing are described below:

- Handle missing value: Dealing with missing values in ML refers to filling in the gaps in the data, which guarantees the quality and stability of the model. Although the fundamental methods are the same (deletion and imputation), the recent developments and factors relate to a more developed approach that is founded on the character of the missing data and its possible effects on the model.
- Removing Duplicate Images: The need to remove duplicate images in machine learning denotes the effort to determine and remove similar or nearly similar pictures within a dataset by methods such as image hashing, pixel-wise comparison, and similarity metrics of the structure of images. This is a very important preprocessing task that helps to avoid model bias, increase efficiency and shorten the training process since each unique visual concept is represented sufficiently.
- Reduce Noise: Noise Reduction focuses on the mechanism of elimination or suppressing any unwanted noise of different signals, especially on audio and images to improve clarity and quality.
- Data Augmentation: Data augmentation is a machine learning method that uses algorithmic generation to artificially grow a dataset by generating new and altered versions of data already present. Particularly useful when dealing with small or skewed real-world data sets, it augments the model's generalizability, reduces overfitting, and boosts performance by adding more variables and larger datasets to the original data.

### *3.3. Min-Max Normalization*

Normalization of the records was done through the min-max method to ensure that values are restricted to a range of 0 to 1. This has been done in a bid to maximize the performance of the available classifiers and to counter the influence of outliers. Normalization was performed based on the mathematical formula (1) as shown below:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \ldots\ldots (1)$$

In where X represents the initial feature value, $X'$stands for the normalized value, $X_{min}$ represents the feature's minimum, and $X_{max}$ represents its maximum.

### *3.4. Feature Extraction*

Feature extraction transforms raw data into a smaller, more informative set of new features, simplifying data complexity and improving machine learning model performance and efficiency by retaining essential information. Feature extraction is an ML and data preprocessing technique that transforms raw data into a set of informative, new features, reducing dimensionality and simplifying the data for improved model performance. This is done by developing new, condensed features by integrating and altering original variables, not merely by selecting a subset of the existing variables, to come up with more efficient and accurate models.

### *3.5. Data Splitting*

The dataset was divided into a 70:30 ratio in training and testing set and the distribution of the classes was ensured to be the same as the original.

### *3.6. Proposed Recurrent Neural Network (RNN) Model*

A model for healthcare disease diagnosis utilizing ECG data is proposed, which is based on DL and uses an RNN. Since RNN units are built to memorize previous states, RNN models are able to handle sequential data with ease [25]. In order to calculate the current state, this memory attribute was utilized [26][27]. So, RNN units take in two values: the current input value and the output from before. One way to describe how RNN units function is as (2).

$$y(t) = f\big(x(t) + y(t-1)\big) \ldots\ldots (2)$$

When $x(t)$ is the input, $y(t)$ is the output, and $y(t-1)$ is the output from before. To represent this relationship, have a function $(x)$. The nonlinearity caused by the function $(x)$ in RNN is owing to its unstable gradient tendency; it is a simple hyperbolic tangent function. The application of the rectified linear unit function or any other non-saturating activation function leads to arbitrary big gradients. As demonstrated in 4, this model made use of a dense layer, two recurrent layers, and a single input layer.

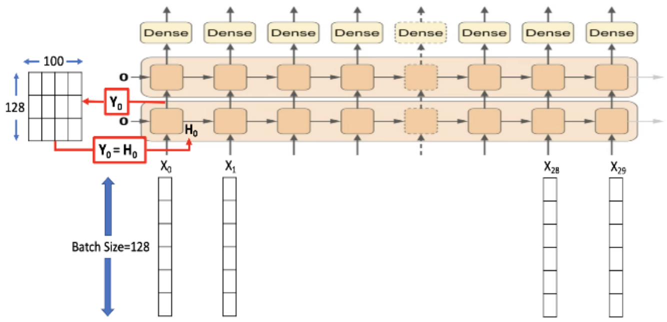


**Fig 4: RNN Model Structure**

There is a maximum batch size of 128 that the recurrent layers manage. A recurrent layer is a 100-unit structure that consists of 30-time steps. A single value for the predicted number of questions is produced by the dense layer using the outputs from the recurrent layers. This design uses RNN units to store and transmit state information to subsequent iterations. There are a few drawbacks to stateful RNN models: they take longer to train, and they don't always do well on longer sequences due to high correlation between batches.

### *3.7. Evaluation metrics*

Several performance measures were used to assess the efficient operation of the suggested layout. A confusion matrix was generated to present the classification outcomes, which include the total number of correct and incorrect guesses for every class. Accurate Positives (TP), Accurate Negatives (TN), and False Negatives (FN) were calculated from this matrix. Following the steps described below, important performance measures like ACC, PRE, REC, and F1 were calculated using these values:

Accuracy: A measure that compares the trained model's prediction performance to the full dataset, or input samples. The equation is (3)-

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+Fp+TN+FN}} \ldots\ldots (3)$$

Precision: The ACC is the proportion of properly predicted positive cases to the total number of positive examples, and it measures the accuracy rate of a model's predictions. PRE denotes. The classifier's predictive power for positive classifications can be expressed as (4)-

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \ldots . (4)$$

Recall: The accuracy of positive event predictions relative to the total number of instances that ought to have been positive is measured by this number. In mathematical terms, it is expressed as (5)-

$$Recall = \frac{\mathrm{TP}}{TP+FN} \ldots\ldots\ldots (5)$$

F1 score: It is the weighted average of PRE and REC, i.e. it assists in the balancing out of REC and PRE. Its range is [0, 1]. Mathematically, it represented as (6)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \ldots\ldots (6)$$

Receiver Operating Characteristic Curve (ROC): The receiver operating characteristic (ROC) compares the percentage of positive cases identified correctly against the percentage of false positives at different decision cut-off points.. TPR is also sensitivity or REC or FPR = 1-specificity.

## 4. Results and Discussion

In this section, the experimental setup is presented and the performance of the proposed model in both training and testing processes highlighted in addition to its computational efficiency and evaluation. The system analysis and design were conducted on a potent Dell PowerEdge T430 server, having 32 GB of RAM, 8 cores of Intel Xeon processors of 3.4 GHz, 16 logical cores, and a 24 GB NVIDIA Graphical Processing Unit (GPU). Table II shows the essential performance measures for this model, which was trained using the ECG dataset. These metrics include ACC, PRE, REC, and F1. The proposed RNN model of disease diagnosis in healthcare based on the ECG signal shows excellent results with the use of ECG. It has reached a high ACC rate of 99.5, which is a strong reflection of the fact that the model can identify the correct type of case in the vast majority of cases. The model also scored 99.4 in terms of PRE which is its capability to limit the false positives and confidently detect cases of true diseases. The REC of 99.2% demonstrates that the model is very effective in identification of real positive cases, so that not many cases are overlooked. Also, the F1 of 99.2% supports the balanced performance of the PRE and REC and indicates the strength and consistency of the proposed RNN model to predict the disease with high ACC based on ECG signals.

**Table 2: Classification Results of the Proposed Model FOR Disease Diagnosis in Healthcare USING the ECG Dataset**

| Matrix | Recurrent Neural Network (RNN) |
|---|---|
| Accuracy | 99.5 |
| Precision | 99.4 |
| Recall | 99.2 |
| F1-score | 99.2 |

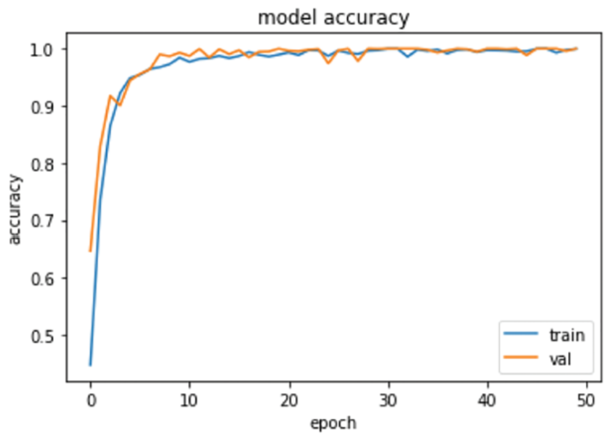


**Fig 5: Accuracy Curve for RNN Model**

Figure 5 displays the model's training and validation performance over 50 epochs. At first, the level of training is rather low (between 45 and 65), which means that the model learns at the beginning. ACC is quickly increasing as the epochs go on and both training, and validation curves are steeply increasing and reaching above 99 percent at the 15th epoch. The fact that the training and validation curves are very close during the epochs implies that the model generalizes to unknown data and there is little overfitting. Overall, the plot demonstrates that the model achieves high and stable ACC, confirming its effectiveness in learning from the ECG dataset.

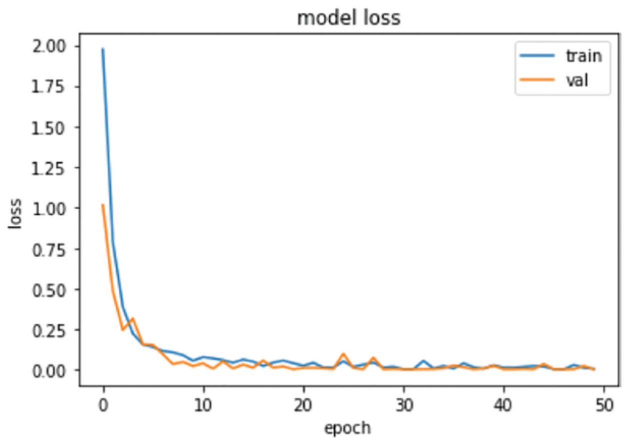


**Fig 6: Loss Curve for the RNN Model**

A machine learning model goes through 50 epochs of training, as shown in Figure 6. Training loss (train) and validation loss (val) both begin at a high value and quickly fall as the model learns, as shown by the blue and orange lines, respectively. There is a considerable flattening of the loss curves after approximately 10 epochs, which indicates that the model has converged. The model is doing well and does not exhibit any noticeable symptoms of overfitting (when validation loss starts to rise substantially while training loss continues to fall) because both losses are very low and stable throughout the remaining epochs, generally hovering close to zero with only minor changes.

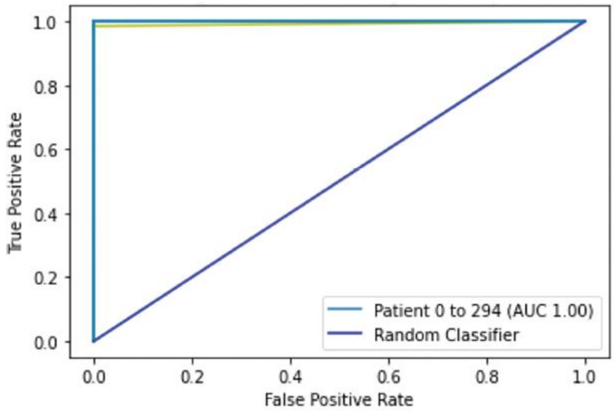


**Fig 7: ROC Curve for RNN Model**

A Receiver Operating Characteristic (ROC) curve, as shown in Figure 7, is a common tool for assessing the efficacy of a binary classification model. The model is considered to be as good as chance if its Area under the Curve (AUC) is 0.50, as shown by the diagonal blue line, which represents a Random Classifier. The model labeled "Patient 0 to 294" is prominently displayed at the top left of the graph, sticking out like a sore thumb with its vivid blue and yellow line. With an accurate detection of all positive cases and zero false alarms, the model achieves a sensitivity of 1.0 and a false positive rate of 0.0, signifying flawless categorization. This model stands out as the top choice for the given dataset, successfully distinguishing between the two groups, with an AUC of 1.00.

### *4.1. Comparative analysis*

The proposed RNN model's effectiveness is evaluated by comparing ACC with different existing models, as shown in Table III. When looking at the ECG dataset side-by-side with several ML and DL models for illness diagnosis, there are noticeable performance gaps. When it comes to identifying ECG signals, the CNN model performs the worst with 49% ACC, 63% PRE, 49% REC, and 42% F1. The RF model outperforms the others significantly; it demonstrates good classification power with an F1 of 84%, REC of 85%, PRE of 82%, and ACC of 83.7%. ResNet50, a deep learning model, shows its capacity to grasp complicated ECG patterns with an F1 of 93.8%, REC of 93.7%, PRE of 94%, and ACC of 94.02%. The RNN is the best of all the models with the highest performance of 99.5% ACC, 99.4% PRE, 99.2% REC, and F1 of 99.2%, which indicates that it is the most effective model when it comes to diagnosing diseases using ECG signals.

**Table 3: Comparison of Different Machine Learning and Deep Models for Disease Diagnosis in Healthcare Using ECG Dataset**

| Model | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| CNN[28] | 49 | 63 | 49 | 42 |
| RF[29] | 83.7 | 82 | 85 | 84 |
| ResNet50[30] | 94.02 | 94 | 93.7 | 93.8 |
| RNN | 99.5 | 99.4 | 99.2 | 99.2 |

The suggested RNN ECG signal classification model demonstrates its possible usefulness in the early disease detection in healthcare since the ACC of the model is high (at 99.5%). A significant improvement over more conventional machine learning methods for dealing with time-series data is the model's ability to accurately depict sequential patterns and temporal dependencies in the ECG signals. It can process continuous cardiac signals and, therefore, identify small abnormalities precisely, which improves the diagnosis of cardiovascular diseases. Moreover, the model is resilient in an extensive array of datasets of patients, which ensures that it can be successfully used in real-world clinical practice, thus it is a convenient tool in regard to timely and precise decisions in healthcare.

## 5. Conclusion and Future Study

Generally, it is imperative to detect cardiac abnormalities accurately and in advance to enhance patient outcomes, reduce healthcare costs, and avert severe complications. The application of RNN, a form of deep learning, can be used for automated ECG signal classification in healthcare, according to another conclusion drawn from this work. The proposed RNN model also reflected the increased ACC of 99.5% which was superior to the baseline models CNN, RF and ResNet50. The model has the capability to identify temporal relations and sequence patterns in ECG signals that enable it to identify small anomalies which would otherwise have been ignored by traditional methods hence facilitating timely and credible clinical decision making. The future work may be spent on the combination of multimodal patient information, i.e. wearable sensor information, echocardiogram, and laboratory results that will further increase the level of diagnostic ACC and patient monitoring. In addition, the implementation of lightweight and real-time RNN architecture can be trained to be implemented in the resource-constrained clinical environment. Research on explainable AI and model interpretability is also expected to increase clinician confidence and adoption to enable automated ECG analysis to become a useful tool in everyday clinical practice. These technologies can radically play a role in the early diagnosis of the disease and the general healthcare provision of the heart.

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