Journal of Contemporary Science and Technology Management
Volume 02, Issue 01, March 2026

Early Diagnosis of Heart Conditions Using AI-Driven on Electronic Health Data

Krishna Bhardwaj Mylavarapu[1], Jenitha Pilli[2], Prathik Kumar Jannu[3], Javed Ali Mohammad[4], Sri Harsha Panchali[5], Usha Mohani Kavirayani[6]

[1] MS in Computer Science, University of Illinois Springfield
[2] MS in Computer Science, University of Louisiana at Lafayette
[3] Computer Science Engineering, JNTU Hyderabad
[4] Masters in Data Science, New England College
[5] Information Systems Engineer, CrowdStrike Inc
[6] MS in Computer Science, Kent State University

Abstract

Heart failure, atherosclerosis, coronary artery disease, cardiomyopathies, arrhythmic disorders, valve diseases, and other cardiovascular diseases (CVDs) are the main causes of illness and death around the world. This work presents a practical method that uses deep learning to detect cardiac problems early using electrocardiogram (ECG) readings. It uses the ECG Heartbeat Categorization Dataset of Kaggle based on the MIT-BIH Arrhythmia Database which has more than 109,000 labeled ECG segments in five classes of heartbeats. Extensive data preprocessing is done, such as data cleaning, Z score normalization, one-hot encoding, and recursive feature elimination (RFE) of feature selection. As a measure to deal with a sharp disparity in the classes, the ADASYN oversampling method is used, with a balanced dataset being obtained. After that, a Recurrent Neural Network (RNN) is trained on the time-dependent nature of electrocardiogram (ECG) signals in order to identify heartbeats accurately. The accuracy (ACC), precision (PRE), recall (REC), F1-score (F1), and loss are the measures used to assess the performance of the model. With scores of 96.06% for accuracy, 90.0% for precision, 93.1% for recall, and 91.0% for F1-score, the suggested RNN model shows good performance, suggesting balanced and reliable categorization. Early cardiac problem detection and clinical decision-making may benefit from the proposed RNN technique, since it beats both conventional ML algorithms and rival deep learning architectures.

Keywords: Cardiovascular Diseases, ECG Signal Analysis, Arrhythmia Classification, Deep Learning, Early Diagnosis, Clinical Decision Support.

DOI: 10.66592/jcstm.02.01.03

I. Introduction

The healthcare industry contributes greatly to emissions and wastages of carbon. Plastic, paper, and electronic waste are some of the non-biological waste that form a substantial part of the waste. Plastic production and incineration is estimated to have produced 850 million tons of greenhouse gases, and it is likely to reach 2.8 billion tons by 2050. The healthcare sector has been known to be a significant source of the climate crisis, which is cited as the biggest threat [1] to the health of the 21st century [2]. Technological progress and information systems are reshaping industries, including healthcare, with an eye towards integrated systems. Improving healthcare quality while reducing costs is the primary goal of most healthcare system reforms. There is a dearth of sufficient systems among healthcare professionals and institutions to implement strategic change [3]. Therefore, they are under a great deal of pressure to make use of IT.

Cardiology is a wide field of clinical medicine including clinical research, associated with cardiovascular disease and stroke. There has been rapid progress in understanding of cardiovascular diseases [4], with advances in epidemiology, pathophysiology, clinical studies, data science, artificial intelligence and health economics and modelling. Myocardial structural and functional defects that impede ventricular filling or blood ejection cause the clinical condition known as heart failure (HF). Although heart failure can be caused by pericardial, myocardial, endocardial, heart valve, or severe vascular dysfunction, the most common cause is a decrease in left ventricular myocardial function [5]. Inherited heart failure causes include ventricular remodelling, increased haemodynamic overload, ischaemia-related dysfunction, aberrant myocyte calcium cycling, inappropriate extracellular matrix proliferation, accelerated apoptosis, genetic mutations, and excessive neuro-humoral stimulation.

A myocardial infarction risk can be kept to a minimum by finding cardiovascular illnesses (CVDs) quickly and correctly. Due to the complexity, lack of clarity, and nonlinearity of the relationships between CVD variables, artificial intelligence tools are necessary. Predicting and categorising CVDs are made easier using these technologies. Arrhythmia, problems with blood vessels, heart failure, myocardial infarction, strokes, and other cardiac abnormalities are all part of CVDs, which are among the top causes of death globally. Some groups estimate that more than 17 million people died from these causes in 2019, accounting for nearly 30% of all deaths globally that year. Therefore, in healthcare, especially for CVDs, it is crucial to detect diseases quickly and accurately and identify the main risk factors. A number of algorithms for risk prediction have been proposed, with regression methods integrating data through known risk factors being the most common. To make matters worse, current approaches fail to account for the nonlinear nature and complexity of risk variables, which significantly impact CVD prediction even when these factors do not interact with each other.

AI and ML have the potential to reduce mortality by predicting heart attacks using a patient's health and medical history. ML is a versatile approach with many potential uses. Its effect on the detection of cardiac diseases is also shown. The use of ML to forecast heart attacks was the subject of several studies. ML has the ability to provide accurate forecasts and decision-supporting capabilities [6]. In order to learn from past data and create predictions based on current data, ML algorithms are employed. Algorithms can process big data, allowing for the extraction of valuable insights. Deep learning in medical settings that can be rare by nature is limited by nature and is not dependent on the amount of training data. The hypothesis is that through the input data that was filtered according to clinical guidelines, that is, through the choice of five unique perspectives of the cardiac examination, the algorithms could be made to recognize diagnostic clues even in case of a limited size database.

A. *Motivation and Contribution of Paper*

Conventional statistical methods fail to give a fair representation of the time patterns of electrocardiograms (ECGs) in imbalanced and rare cases, and the nonlinear and complex nature of cardiac risk factors makes cardiovascular disease diagnosis a challenging task. Current diagnostic measures do not always yield early diagnosis which is reliable and hence heightens clinical risk and health care burden. The study is guided by the necessity of smart and data-driven decision support systems based on deep learning to model the dynamics of ECG effectively, enhance diagnostic ACC, provide timely clinical intervention to manage cardiovascular diseases sustainably and efficiently. The key contributions of the study are listed below:

- An efficient method for classifying arrhythmias using deep learning and a large ECG heartbeat classification dataset derived from the MIT-BIH Arrhythmia Database.
- Development of a comprehensive preprocessing pipeline incorporating data cleaning, Z-score normalization, one-hot encoding, and RFE-based feature selection.
- The ADASYN oversampling technique effectively improves minority class representation while handling extreme class imbalance.
- A RNN used to model temporal variations in ECG based heartbeat classification.
- Testing the model's stability and balance on a large scale using conventional metrics like REC, ACC, PRE, F1, and loss.

B. *Significance of the Study*

The research has value because it shows how recurrent neural networks can be used to predict temporal relationships in the ECG signal with strong ACC and early detection of heart diseases. The proposed method overcomes major issues related to data imbalance and sophisticated variability of signals that tend to hinder clinical analysis of ECGs, including the need to balance the classes with the adaptive use of ADASYN and the element of selecting the features that enhance the analysis of the data. The obtained high classification performance shows that the model may be valuable to clinicians by enabling them to detect cardiac abnormalities at an early stage and with high reliability to ensure timely intervention and better patient outcomes. In addition, the relative excellence of the RNN, compared to the traditional and hybrid models, indicates its appropriateness in real-world, sequential healthcare data, which can advance intelligent and data-driven clinical decision support systems.

C. *Structure of paper*

The following is the outline of the paper: In Section II, take a look at what is already known about how to spot heart problems early. Section III defines the recommended methodology that implemented which entail the description of the data and the implementation of the model. In the section IV, the results and main findings of the experiment are provided. In the end, Section V provides the conclusion of the study, outlining its limitations and providing future research directions.

II. Literature Review

This is a literature review that gives an in-depth insight into the available literature and evidence regarding Early Diagnosis of Heart Conditions. Table I presents the methods, database, outcomes, limitations and future direction of the literature.

Gupta et al., (2019) In this regard, KNN utterly dominates its rivals, which comprise RF, DTs, NBs, and SVM. The findings are further validated by creating a prototype. In order to track a person's vitals and identify potential risk factors for cardiovascular disease, the prototype used a network of sensors. Making use of the previously trained model to forecast a person's risk of cardiovascular disease is an attainable objective. Their approach has a high predictive ACC of 88.52% and allows proactive health monitoring data, both of which are substantial benefits to humans [7].

Journal of Contemporary Science and Technology Management
Volume 02, Issue 01, March 2026

Mohan, Thirumalai and Srivastava, (2019) presented a new approach to improve the accuracy of cardiovascular disease prediction using machine learning to identify important characteristics. Use a variety of feature combinations and established categorisation approaches to establish the foundation for the prediction model. They achieved an ACC of 88.7 % while predicting the occurrence of cardiac disease using a HRFLM [8].

Raihan et al., (2018) ML methods are better at making predictions than any other type of system. Forecasting the likelihood of tachycardia is the primary objective of this approach. Use methods like Neural Networks, Support Vector Machines, AdaBoost, Bagging, K-NN, and Random Forests to predict when ACS betrayed. Both AdaBoost and Bagging achieve high-grade exactness, with 75.49% and 76.28% respectively. For Bagging techniques, AdaBoost has a REC of 0.763 and a PRE of 0.741, while for Bagging techniques it is 0.75 and 0.755, respectively [9].

David and Belcy, (2018) The major objective of this extensive research is to identify the best classification system for reliably differentiating between healthy and unhealthy persons. This allows for the saving of lives to occur as quickly as possible. The algorithms' performance evaluated in a testing environment that has been set up using the UCI machine learning repository's cardiac disease benchmark dataset. With an ACC of 81%, the RF approach outperforms other algorithms when it comes to heart disease prediction [10].

Karayılan and Kılıç, (2017) Conventional methods of diagnosis fall short when it comes to this type of sickness. The conventional method of diagnosing heart disease is outperformed by a medical diagnosis system built on ML. The paper details a method for predicting the start of cardiac problems using an ANN and the backpropagation algorithm. After being trained with thirteen clinical features and the backpropagation approach, the neural network achieved a 95% ACC rate in detecting the presence or absence of heart disease. [11].

Miao, Miao and Miao, (2016) The tested models for CCF, HIC, LBMC, and SUH had accuracies of 80.14%, 81.1%, 88.1%, and 96.7%, respectively. The levels of accuracy were higher than those found in earlier studies. Patients around the world, particularly in underdeveloped nations and places with a shortage of cardiac disease diagnostic experts, can benefit from the reliable and accurate diagnoses provided by the well-established ensemble learning prediction and classification models for coronary heart disease [12].

Research Gap: Although the situation has greatly improved in predicting heart disease, there is still a number of uncovered gaps. The majority of existing approaches rely on static and feature-based models, which are inadequate for describing the intricate temporal patterns and nonlinearities present in natural physiological signals. There are still issues of imbalance in classes, a lack of generalization and poor treatment of rare clinical cases. This demonstrates the importance of powerful, temporally conscious deep learning systems that can combine powerful feature selection and effective balancing to ensure sound early detection

TABLE I. SUMMARY OF RECENT STUDIES ON EARLY DIAGNOSIS OF HEART CONDITIONS

Reference	Methodology	Dataset	Key Findings	Challenges	Future Scope
Gupta et al. (2019)	KNN compared with RF, DT, SVM, NB; prototype using health sensors	Sensor-based health monitoring data	KNN outperformed other models with 88.52% accuracy; enabled proactive health monitoring	Limited scalability and reliance on sensor accuracy	Integration with larger clinical datasets and real-time deployment
Mohan et al. (2019)	HRFLM and feature combinations	Heart disease dataset (clinical features)	Improved prediction accuracy to 88.7% using hybrid model	Feature dependency and model complexity	Automated feature selection and deep learning integration
Raihan et al. (2018)	ML models: NN, SVM, AdaBoost, Bagging, KNN, RF	Acute Coronary Syndrome (ACS) dataset	Best accuracy achieved by Bagging (76.28%) and AdaBoost (75.49%)	Lower accuracy and difficulty handling complex patterns	Advanced ensemble and deep learning models for higher precision
David & Belcy (2018)	Comparative analysis of ML classifiers	UCI Heart Disease dataset	RF achieved 81% precision, outperforming others	Limited dataset size and imbalance	Use of balanced datasets and hybrid learning models
Karayılan & Kılıç (2017)	Artificial Neural Network with backpropagation	Clinical dataset with 13 features	Achieved high accuracy of 95% in heart disease prediction	Risk of overfitting and lack of temporal modeling	Use of recurrent and deep neural networks
Miao et al. (2016)	Ensemble learning classification models	Multiple heart disease datasets (CCF, HIC, LBMC, SUH)	Achieved accuracies up to 96.72%, surpassing prior studies	Dataset heterogeneity and interpretability	Explainable AI and broader validation across populations

Journal of Contemporary Science and Technology Management
Volume 02, Issue 01, March 2026

III. METHODOLOGY

The actual procedure starts by obtaining the dataset of the ECG heartbeat categorization available on Kaggle and undergoing it through the data pre-processing procedure consisting of data cleaning, Z-score normalization, one-hot encoding, and feature selection. In order to deal with class imbalance, data balancing of ADASYN is used. The processed data is then split into two parts: the training data, which makes up 70% of the total, and the testing data, which makes up 30%. The suggested RNN model is trained with the training data and then assessed using metrics like loss, ACC, PRE, REC, and F1. At last, the evaluation results are produced to determine the model's efficacy. The general workflow is shown in Figure 1.

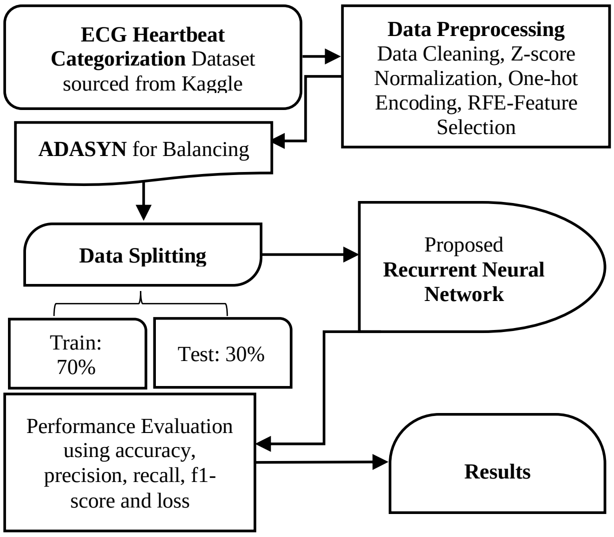

Fig. 1. Flowchart Diagram for Early Diagnosis of Heart Conditions

The steps of the flowchart are thoroughly explained below:

A. *Data Collection and Visualizations*

In this work, ECG Heartbeat Categorization Dataset of Kaggle, based on the MIT-BIH Arrhythmia Database, that is pre-processed ECG segments where heartbeat classes are categorized into five and has more than 109, 000 samples to classify arrhythmia data is used. The EDA of the dataset is shown below:

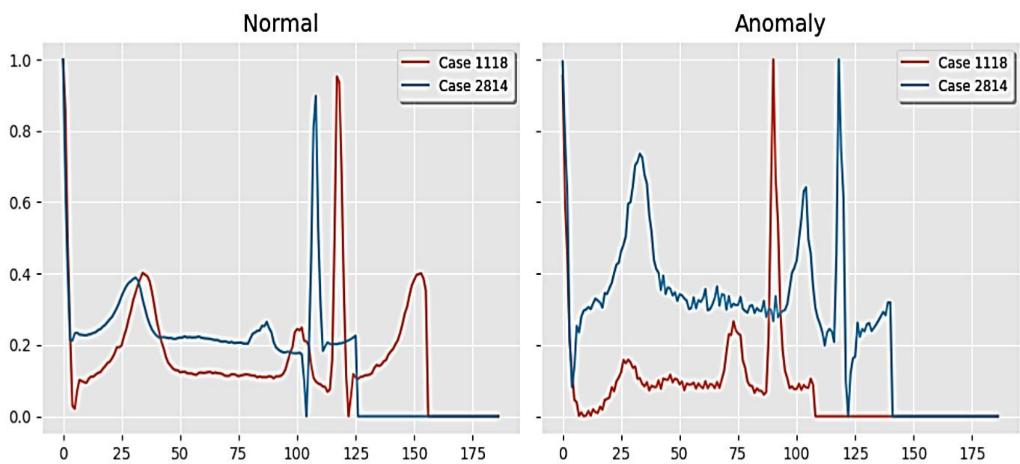

Fig. 2. ECG Signal Samples One From the "Normal" Dataset and the Other From the "Anomaly" Dataset.

Figure 2 presents ECG signals in a normal and abnormal heartbeat, where normal signals have regular shapes, whereas abnormal signals have irregular shapes and amplitude changes and can be easily distinguished between normal and illnesses.

Journal of Contemporary Science and Technology Management
Volume 02, Issue 01, March 2026

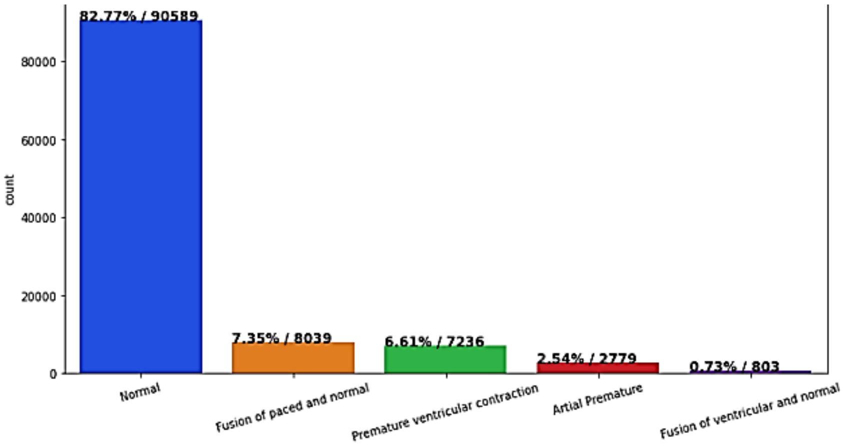

Fig. 3. Heartbeat Classes Distribution

Figure 3 shows the classes of heartbeat in the dataset. It presents a high degree of imbalance in terms of classes with normal heartbeats being the most common samples with many other abnormal classes being much rarer with premature ventricular contractions, atrial premature beats and fusion beating. The lack of balance reflects the difficulty of precisely identifying rare cardiac diseases and the significance of effective learning models to be used to diagnose the condition at an early stage.

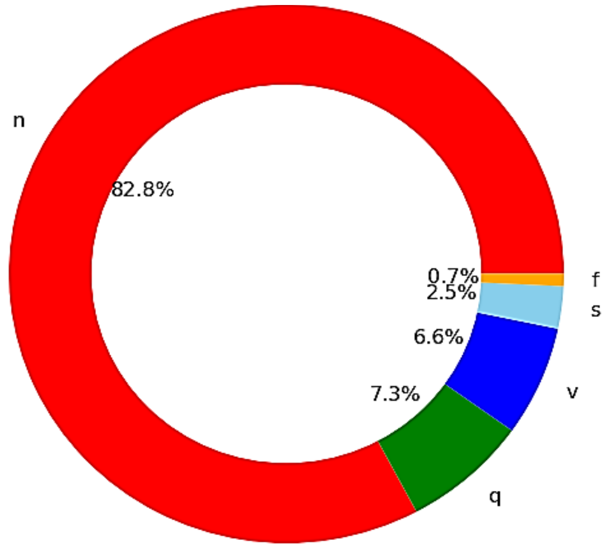

Fig. 4. Imbalanced Distribution in the Dataset

Figure 4 shows a donut chart of the distribution of the categories of heartbeat by the classes. The plot shows that the normal heartbeats are dominant in the dataset whereas the abnormal classes, that is, fusion beats, premature ventricular contractions, atrial premature contractions and paced beats are much lower in the dataset, determination of the class imbalance in the dataset.

B. Data Preparation

Cardiovascular datasets used in ML models rely heavily on data pre-processing. It starts by cleaning data, normalizing data, and selecting RFE-features.

- **Data Cleaning:** Resolving issues with inconsistent or missing data. When data from wearable devices or electronic health records (EHRs) is missing, imputation and similar techniques fill in the blanks with more commonly used values, such as the median, mean, or prediction scores.
- **Z-score normalization:** Data is normalised to ensure that all variables are scaled to the same ranges, preventing outliers like heart rate and blood pressure from influencing ML models. Utilise a method such as z-score normalisation to train a model using features with a mean of 0 and a standard deviation of 1. Its definition is in Equation. (1):

Journal of Contemporary Science and Technology Management

Volume 02, Issue 01, March 2026

$$z = \frac{x-\mu}{\sigma} \quad (1)$$

Each feature's distribution becomes one with a mean of 0 and a standard deviation of 1 after this transformation.

- **One-Hot Encoding:** ML algorithms can make use of numerical formats created by converting categorical data, which is otherwise non-numerical, into a numerical representation. Each category of each categorical feature is given its own new binary column by the one-hot encoding.
- **RFE-Feature Selection:** RFE algorithm was proposed where gene selection in disease classification was involved. RFE uses the recursive method, which is a backward feature elimination. RFE has proven itself as a useful feature selection method, which presents the benefits of dimensionality reduction, better model ACC and interpretability, and higher computational efficiency compared to exhaustive feature assessments.

C. *ADASYN for Balancing the Class Distribution*

One synthetic oversampling method that uses SMOTE is ADASYN. The goal of ADASYN is to generate synthetic examples for harder-to-learn minority class cases. It does this by adaptively changing the distribution of synthetic samples according to the instances' density distribution. As part of its synthetic sample generation process, ADASYN estimates the minority class instances' density distribution and gives preference to those with a lower density. This highlights the areas that need more attention since synthetic sample generation is focused on instances that are hardest to understand. The limitation of SMOTE that ADASYN has been created to overcome is that the sample synthesis is adjusted adaptively in situations where the imbalance between the two classes is more extreme or where the minority class examples are scattered in intricate structures. ADASYN attempts to find a more optimal balance between overfitting and oversampling the minority population. Figure 5 shows the balanced data distribution.

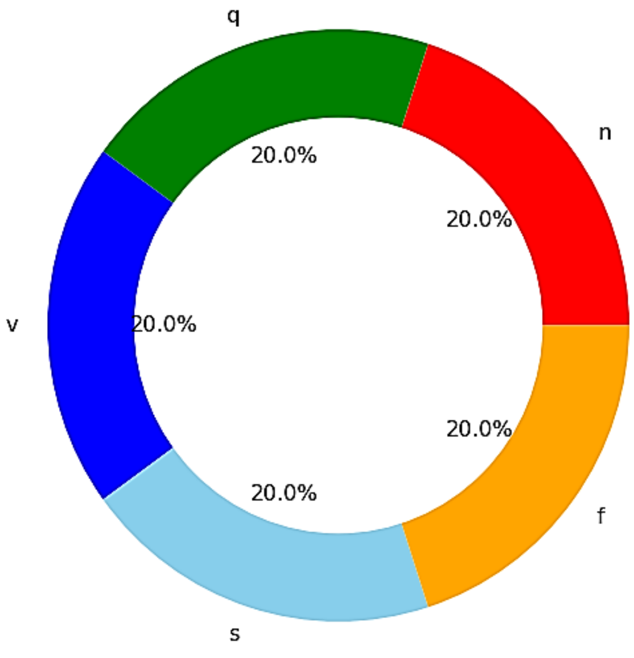

Fig. 5. Balanced Distribution in the Dataset

Figure 5 displays a balanced distribution of the classes with the help of donut chart and each heartbeat category is equally contributing to the total number of heartbeats. Such a representation helps to show the impact of data balancing algorithms, where there equal representation of the classes and the bias is minimized when training the model to boost and fair classification.

D. *Data Splitting*

The standard split between training and test sets in a dataset is 70:30, with the former used to train the model and the latter for testing.

E. *Proposed Model: Recurrent Neural Network (RNN)*

An RNN may learn the dynamics of sequential data because it is a neural network architecture with cyclic connections. The buried layer of an RNN contains several nodes. In Figure 6, can observe that each node can produce its own hidden state h_t and output y_t by applying the following Equations to its current input x_t and its past hidden state h_{t-1}. two (2)-(3):

Journal of Contemporary Science and Technology Management

Volume 02, Issue 01, March 2026

$$h_t = \mathcal{F}(W_h h_{t-1} + U_h x_t + b_h) \quad (2)$$

$$y_t = \mathcal{F}\left(W_y h_t + b_y\right) \quad (3)$$

with W_h, U_h and W_y representing the weights for the link between hidden and input, hidden and output, and hidden and hidden, respectively. The hidden state bias term is b_h, while the output state bias term is b_y. Furthermore, every node is linked to an activation function $\mathcal{F}$ [13]. Rectified linear unit (ReLU), sigmoid, and hyperbolic tangent are common examples of element-wise non-linearity functions.

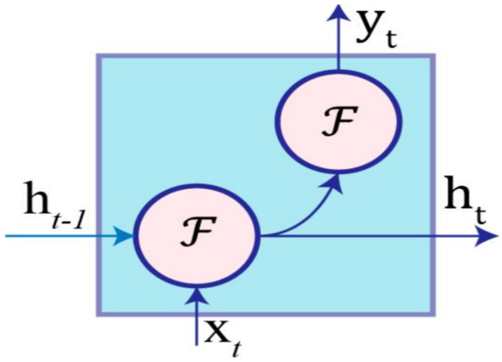

Fig. 6. Schematic Diagram of an RNN

F. *Model Performance Assessment*

The suggested models were evaluated using four popular metrics: binary and multi-class classification:

Accuracy: The sum of all correct guesses divided by the total number of predictions. This can be seen in the Equation as a mathematical representation. (4):

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (4)$$

Precision: Refers to the count of genuine samples among the ones that are classified as positive. Equation (5) depicts the formula:

$$\text{Precision} = \frac{TP}{TP=FP} \quad (5)$$

Recall: A class's REC is the percentage of correctly sampled items from that class. As demonstrated in Equation (6), the total REC is calculated by averaging the RECs for all classes:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (5)$$

F1-Score: The PRE and REC are balanced out by a weighted harmonic mean. It is formulated in Equation (7):

$$F1 - score = \frac{2TP}{2TP+FP+FN} \quad (7)$$

Loss: Loss is a scalar operation that measures the distance between the model predictions and the actual targets of one example (or batch) to provide a guide (optimization) to the training process.

IV. Results Analysis And Discussions

An 8GB RAM, 2.30GHz Intel Core i5 8th generation computer is used for the experiment. The Anaconda Python 3.7 environment is utilised, together with the IDEs Spyder and Jupyter Note Book. The results of the RNN model for the early detection of cardiac problems are shown in Table II. The model has high ACC (96.06%), which shows that it has great overall prediction strength. The summarized REC (93.0) of positive cases indicates successful identification of positive cases, whereas the PRE (90.0) and F1 of positive cases (91.0) indicates a balanced and dependable classification characteristic, which can be used in clinical decision-making during its initial phase.

TABLE II. Model Performance for Early Diagnosis of Heart Conditions

Metrics	**RNN**
Accuracy	96.06
Precision	90.0
Recall	93.0
F1-Score	91.0

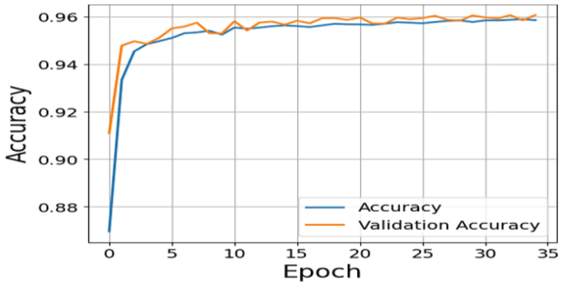

Fig. 7. Accuracy of the RNN Model

Figure 7 shows the relationship between the number of epochs and the account-based cost (ACC) in training and validation. The suggested model learns consistently, converges well, and performs well at generalisation, as shown by the nearly identical training and validation curves, and by the rapid increase in ACC from the beginning stages, which nearly approaches 96.

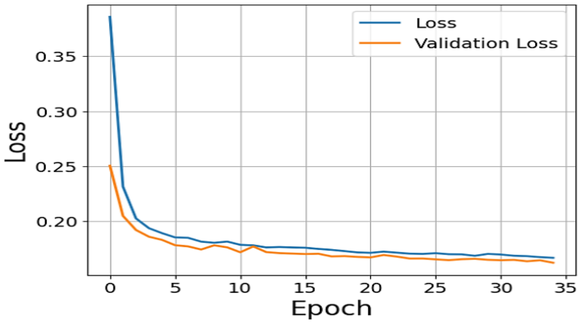

Fig. 8. Loss Curve of the RNN Model

Figure 8 displays the training and validation loss curves across the epochs. It can be observed that the loss decreases significantly during the initial training stages and then stabilises afterwards. Training and validation loss is close, which means that the proposed model is trained successfully with a minimum overfitting rate and a good generalization rate.

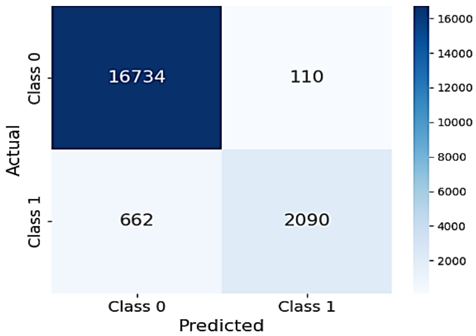

Fig. 9. Confusion Matrix of the RNN Model

A high degree of classification, together with high numbers of true negatives (16,734) and true positives (2,090), are shown in Figure 9, which is the confusion matrix of the proposed model.

A. Comparative Analysis

Table III shows a comparative analysis of the model ACC of early diagnosis of heart conditions. The RNN model outperformed all other models benchmarking models likely 1D-CNN, and RF with a 96.06 % accuracy rate, making it the best choice for learning health data's temporal connections.

TABLE III. COMPARISON OF EARLY DIAGNOSIS OF HEART CONDITIONS

Models	Accuracy
1D-CNN [14]	86%
RF (Model 2) [15]	80.65
RNN	96.06

The experimental findings show that the proposed RNN-based solution is an effective learning solution to identify temporal patterns in electronic health records resulting in trusted early prediction of cardiac problems. The trends of training and validation strategies show that there is no significant overfitting with convergence maintained at a stable rate. Clinical decision assistance and sequential analysis of health data are two areas where the RNN model has shown to be more effective than other deep learning architectures and more conventional machine learning methods.

V. CONCLUSION AND FUTURE WORK

The capacity to identify people who are at risk of CVD is a crucial aspect of preventive cardiology. At present, professional recommendations advise using risk prediction models that rely on a small set of variables that do not always work well with all patient populations. In this study, show that by utilising ECGs, a deep learning-based system may successfully identify cardiac problems in their early stages. The proposed system is able to capture hidden and the complex patterns found in cardiac signals, which are usually missed in the traditional diagnostic data, by using the time modeling ability of a RNNs. The experimental findings suggest the robust and consistent performance and a high percentage of 96.06 classification ACC, as well as equalized values of PRE, REC, and F1 of the proposed RNN model. These findings corroborate that the model is capable of correctly differentiating between normal and non-normal heartbeats, even when there is a lack of signal balance and variability. The RNN model outperforms both conventional machine learning techniques and various other DL architectures, according to the comparative study. Competing with more conventional deep learning architectures and more conventional machine learning approaches.

Further development of the work will entail generalizing the suggested RNN architecture with other more sophisticated models such as LSTM and attention models, introducing multi-lead ECG and real-time streaming input, and testing the model on various clinical datasets to increase its strength, interpretability, and applicability to real-life clinical decision support systems.

REFERENCES

[1]. S. Malallah, Y. Zalah, and R. Karne, "An Analysis of the Advanced Encryption Standard and Threats Associated," 2018, doi: 10.13140/RG.2.2.34873.88168.

[2]. R. Adams, S. Jeanrenaud, J. Bessant, D. Denyer, and P. Overy, "Sustainability-oriented Innovation: A Systematic Review," *Int. J. Manag. Rev.*, vol. 18, no. 2, pp. 180–205, Apr. 2016, doi: 10.1111/ijmr.12068.

[3]. M. Fiaz, A. Ikram, and A. Ilyas, "Enterprise Resource Planning Systems: Digitization of Healthcare Service Quality," *Adm. Sci.*, vol. 8, no. 3, 2018, doi: 10.3390/admsci8030038.

[4]. Renshaw, Laura, and S. K., "An interesting appearance of Ofuji's disease on a F18 FDG PET/CT scan.," *EBSCO*, no. 8, 2013.

[5]. A. A. Inamdar and A. C. Inamdar, "Heart Failure: Diagnosis, Management and Utilization," *J. Clin. Med.*, vol. 5, no. 7, 2016, doi: 10.3390/jcm5070062.

[6]. S. Garg, "Predictive Analytics and Auto Remediation using Artificial Inteligence and Machine learning in Cloud Computing Operations," *Int. J. Innov. Res. Eng. Multidiscip. Phys. Sci.*, vol. 7, no. 2, 2019, doi: 10.5281/zenodo.15362327.

[7]. A. Gupta, S. Yadav, S. Shahid, and V. U., "HeartCare: IoT Based Heart Disease Prediction System," in *2019 International Conference on Information Technology (ICIT)*, 2019, pp. 88–93. doi: 10.1109/ICIT48102.2019.00022.

[8]. S. Mohan, C. Thirumalai, and G. Srivastava, "Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques," *IEEE Access*, vol. 7, pp. 81542–81554, 2019, doi: 10.1109/ACCESS.2019.2923707.

[9]. M. Raihan *et al.*, "A Comprehensive Analysis on Risk Prediction of Acute Coronary Syndrome Using Machine Learning Approaches," in *2018 21st International Conference of Computer and Information Technology (ICCIT)*, 2018, pp. 1–6. doi: 10.1109/ICCITECHN.2018.8631930.

[10]. H. B. F. David and S. A. Belcy, "Heart Disease Prediction Using Data Mining Techniques," Ictact J. Soft Comput.," *ICTACT J. SOFT Comput.*, vol. 9, no. 1, pp. 1824–1830, 2018, doi: 10.21917/ijsc.2018.0254.

[11]. T. Karayılan and Ö. Kılıç, "Prediction of heart disease using neural network," in *2017 International Conference on Computer Science and Engineering (UBMK)*, 2017, pp. 719–723. doi: 10.1109/UBMK.2017.8093512.

[12]. K. H. Miao, J. H. Miao, and G. J. Miao, "Diagnosing Coronary Heart Disease Using Ensemble Machine Learning,"

Int. J. Adv. Comput. Sci. Appl., vol. 7, no. 10, pp. 30–39, 2016.
[13]. A. Murad and J.-Y. Pyun, "Deep Recurrent Neural Networks for Human Activity Recognition," *Sensors*, vol. 17, no. 11, 2017, doi: 10.3390/s17112556.
[14]. B. Pyakillya, N. Kazachenko, and N. Mikhailovsky, "Deep Learning for ECG Classification," *J. Phys. Conf. Ser.*, vol. 913, p. 012004, Oct. 2017, doi: 10.1088/1742-6596/913/1/012004.
[15]. F. I. Alarsan and M. Younes, "Analysis and classification of heart diseases using heartbeat features and machine learning algorithms," *J. Big Data*, vol. 6, no. 1, 2019, doi: 10.1186/s40537-019-0244-x.

[16]. Waditwar, P. (2026) De-Risking Returns: How AI Can Reinvent Big Tech's China-Tied Reverse Supply Chains. Open Journal of Business and Management, 14, 104-124. doi: 10.4236/ojbm.2026.141007
[17]. Padur, S. K. R. (2025). Automation-First Post-Merger IT Integration: From ERP Migration Challenges to AI-Driven Governance and Multi-Cloud Orchestration. *Int. J. Sci. Res. Sci. Eng. Technol*, *12*(5), 270-280.
[18]. Prajkta Waditwar. Agentic AI and sustainable procurement: Rethinking anti-corrosion strategies in oil and gas. World Journal of Advanced Research and Reviews, 2025, 27(03), 1591-1598. Article DOI: https://doi.org/10.30574/.
[19]. Zeeshan, M., Bhadauria, K., Pahal, L., Nagrath, P., & Kalla, D. (2025, June). Ensemble-Based Deep Learning for Automated Diabetic-Retinopathy Detection Using CNNs and Transfer Learning. In *International Conference on Data Analytics & Management* (pp. 216-228). Cham: Springer Nature Switzerland.
[20]. Prajkta Waditwar. Quantum-Enhanced Travel Procurement: Hybrid Quantum–Classical Optimization for Enterprise Travel Management. World Journal of Advanced Engineering Technology and Sciences, 2025, 17(03), 375-386. Article DOI: https://doi.org/10.30574/.
[21]. Routhu, K. K. Next-Generation Workforce Planning: AI-Enabled Forecasting and Strategic HR in Mergers and Acquisitions. *J Artif Intell Mach Learn & Data Sci 2025*, *3*(4), 2962-2967.
[22]. Prajkta Waditwar. Reimagining procurement payments: From transactional bottlenecks to strategic value creation. World Journal of Advanced Research and Reviews, 2025, 28(01), 588-598. Article DOI: https://doi.org/10.30574/.
[23]. Waditwar, P. (2024) AI for Bathsheba Syndrome: Ethical Implications and Preventative Strategies. Open Journal of Leadership, 13, 321-341. doi: 10.4236/ojl.2024.133020
[24]. NR, A. R., Rajasri, T., Praveen, R., Kalla, D., Bendale, S. P., & Venu, N. (2025, April). CAC Training-A Unified Cybersecurity Training Program for Military Staff. In *2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)* (Vol. 3, pp. 569-573). IEEE.
[25]. Aggarwal, A., Agarwal, L., Rella, B. P. R., Nagpal, N., Kalla, D., & Sharma, M. (2025, June). A Performance Comparison of Machine Learning Models for Rain Prediction. In *International Conference on Data Analytics & Management* (pp. 319-328). Cham: Springer Nature Switzerland.
[26]. Padur, S. K. R. (2025). The future of enterprise ERP modernization with AI: From monolithic systems to generative, composable, and autonomous platforms. *J. Artif. Intell. Mach. Learn. & Data Sci*, *3*(1), 2958-2961.
[27]. Routhu, K. K. (2025). From Reactive to Predictive: A Strategic Framework for Attrition Analytics with Oracle 23AI. *European Journal of Advances in Engineering and Technology*, *12*(1), 29-34.
[28]. Prabakar, D., Iskandarova, N., Iskandarova, N., Kalla, D., Kulimova, K., & Parmar, D. (2025, May). Dynamic Resource Allocation in Cloud Computing Environments Using Hybrid Swarm Intelligence Algorithms. In *2025 International Conference on Networks and Cryptology (NETCRYPT)* (pp. 882-886). IEEE.
[29]. Nagaraju, S., Johri, P., Putta, P., Kalla, D., Polvanov, S., & Patel, N. V. (2025, May). Smart Routing in Urban Wireless Ad Hoc Networks Using Graph Attention Network-Based Decision Models. In *2025 International Conference on Networks and Cryptology (NETCRYPT)* (pp. 212-216). IEEE.
[30]. Vadisetty, R., Polamarasetti, A., & Kalla, D. (2025, February). Automated AI-Driven Phishing Detection and Countermeasures for Zero-Day Phishing Attacks. In *International Ethical Hacking Conference* (pp. 285-303). Singapore: Springer Nature Singapore.
[31]. Prajkta Waditwar. Overcoming the AI Data Eclipse: Obstacles to the Full Adoption of Artificial Intelligence in the Procurement Technology Sector. World Journal of Advanced Research and Reviews, 2025, 27(03), 1583-1590. Article DOI: https://doi.org/10.30574/.
[32]. Waditwar, P. (2025) Leading through the Synthetic Media Era: Platform Governance to Curb AI-Generated Fake News, Protect the Public, and Preserve Trust. Open Journal of Leadership, 14, 403-418. doi: 10.4236/ojl.2025.143020.

[33]. S. R. Sagili, V. K, B. Puli, P. Sundaramoorthy, M. R and K. N V, "Advancing Cervical Cancer Identification using Generative-based Adversarial Networks: An Integrative Learning Methodology," 2025 6th International Conference for Emerging Technology (INCET), BELGAUM, India, 2025, pp. 1-5, doi: 10.1109/INCET64471.2025.11140170.
[34]. Waditwar, P. (2025) Agentic AI in Contract Analytics Harnessing Machine Learning for Risk Assessment and Compliance in Government Procurement Contracts. Open Journal of Business and Management, 13, 3385-3395. doi: 10.4236/ojbm.2025.135179.
[35]. S. R. Sagili, S. Chidambaranathan, N. Nallametti, H. M. Bodele, L. Raja and P. G. Gayathri, "NeuroPCA: Enhancing Alzheimer's disorder Disease Detection through Optimized Feature Reduction and Machine Learning," 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India, 2024, pp. 1-9, doi: 10.1109/ICEEICT61591.2024.10718628.
[36]. Waditwar, P. (2025) AI-Driven Smart Negotiation Assistant for Procurement—An Intelligent Chatbot for Contract Negotiation Based on Market Data and AI Algorithms. Journal of Data Analysis and Information Processing, 13, 140-155. doi: 10.4236/jdaip.2025.132009.
[37]. Waditwar, P. (2025) Smart Procurement in the Sports Industry: A Strategic Approach for Efficiency and Performance Enhancement. Open Journal of Business and Management, 13, 1743-1761. doi: 10.4236/ojbm.2025.133090
[38]. Waditwar, P. (2025) Transforming Government Procurement through Electronic Bidding—A Case Study on the City of Somerville's Implementation of BidExpress Infotech. Open Journal of Leadership, 14, 165-175. doi: 10.4236/ojl.2025.141007
[39]. Waditwar, P. (2025) AI-Driven Procurement in Ayurveda and Ayurvedic Medicines & Treatments. Open Journal of Business and Management, 13, 1854-1879. doi: 10.4236/ojbm.2025.133096
[40]. Vanaparthi, N. R. (2025). The roadmap to mainframe modernization: Bridging legacy systems with the cloud. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 11(1), 125–133. https://doi.org/10.32628/
[41]. Vanaparthi, N. R. (2025). Why digital transformation in fintech requires mainframe modernization: A cost-benefit analysis. International Journal of Science and Research Archive, 14(1), 1052–1062. https://doi.org/10.30574/
[42]. Vanaparthi, N. R. (2025). Intelligent finance: How AI is reshaping the future of financial services. International Journal of Computer Engineering and Technology, 16(1), 126–137. https://doi.org/10.34218/
[43]. Vanaparthi, N. R. (2025). Regulatory compliance in the digital age: How mainframe modernization can support financial institutions. International Journal of Research in Computer Applications and Information Technology, 8(1), 383–396. https://doi.org/10.34218/
[44]. Venkata, S. S. G. (2025). SECURE SOFTWARE DEVELOPMENT: INTEGRATING ENCRYPTION PROTOCOLS FROM DESIGN TO DEPLOYMENT. International Journal of Applied Mathematics, 38(2s), 1190-1213. https://doi.org/10.12732/ijam.
[45]. Venkata, S. S. G. (2025). From code to cloud: Navigating the future of software engineering and testing automation. International Journal of Basic and Applied Sciences, 14(6), 63–70. https://doi.org/10.14419/
[46]. Venkata, S. S. G. (2025). Audit: Risk Aware Software Security. QTanalytics Publication (Books), 67–75. https://doi.org/10.48001/978-
[47]. Kohli, H., Hadi, A., Mukhi, N., Miah, M. A., & Siddiqa, K. B. (2025). Energy-Aware Intelligent Computing Framework for Sustainable AI Workloads in Next-Generation Smart Systems. International Journal on Smart & Sustainable Intelligent Computing, 2(4), 34-47.
[48]. Routhu, K. K. Next-Generation Workforce Planning: AI-Enabled Forecasting and Strategic HR in Mergers and Acquisitions. *J Artif Intell Mach Learn & Data Sci 2025*, *3*(4), 2962-2967.
[49]. Kohli, H., Hadi, A., Mukhi, N., Miah, M. A., & Siddiqa, K. B. (2025). Energy-Aware Intelligent Computing Framework for Sustainable AI Workloads in Next-Generation Smart Systems. International Journal on Smart & Sustainable Intelligent Computing, 2(4), 34-47.
[50]. Jain, A., Kotha, S. S. M., Bhambri, S., & Kohli, H. (2025, March). Machine Learning Pre-trained Language Models for English-French Neural Machine Translation using Topsis. In 2025 IEEE International Conference on Contemporary Computing and Communications (InC4) (pp. 1-6). IEEE.
[51]. S. R. Sagili, C. Goswami, V. C. Bharathi, S. Ananthi, K. Rani and R. Sathya, "Identification of Diabetic Retinopathy by Transfer Learning Based Retinal Images," 2024 9th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2024, pp. 1149-1154, doi: 10.1109/ICCES63552.2024.10859381.

[52]. Agarwal, K., Bhambri, S., Sridharan, V. K., Mohammed, N., Kohli, H., & Kapoor, J. A. (2025, March). Performance Evaluation of different Machine Learning Techniques for Pothole Detection. In 2025 IEEE International Conference on Contemporary Computing and Communications (InC4) (pp. 1-8). IEEE.
[53]. Kohli, H., Mokashi, S. P., Sundaramoorthy, P., Jangid, D., & Chaganti, K. (2025, July). AI-NLP Framework for Customer Segmentation and Personalized Recommendations in Digital Marketing Environments. In 2025 IEEE 4th World Conference on Applied Intelligence and Computing (AIC) (pp. 146-151). IEEE.
[54]. S. R. Sagili and T. B. Kinsman, "Drive Dash: Vehicle Crash Insights Reporting System," 2024 International Conference on Intelligent Systems and Advanced Applications (ICISAA), Pune, India, 2024, pp. 1-6, doi: 10.1109/ICISAA62385.2024.10828724.
[55]. Waditwar, P. (2024) The Intersection of Strategic Sourcing and Artificial Intelligence: A Paradigm Shift for Modern Organizations. Open Journal of Business and Management, 12, 4073-4085. doi: 10.4236/ojbm.2024.126204.