Enhancing Therapeutic Investigation Through AI Driven Convolutional Neural Network in Comparison with Deep Learning Techniques

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Article Info
Journal of Machine and Computing (https://anapub.co.ke/journals/jmc/jmc.html)
Doi: https://doi.org/10.53759/7669/jmc202505084
Received 28 November 2024; Revised from 15 January 2025; Accepted 07 March 2025.
Available online 05 April 2025.

Abstract – This study seeks to enhance an Artificial Intelligence (AI) system for identifying medical issues using deep learning (DL) techniques. Conventional methods often struggle to predict health conditions and provide effective solutions. A re-modelled convolutional neural network (RCNN) is introduced, featuring optimized activation functions in its convolutional layers and incorporating dense, fully connected layers. The efficiency of the RCNN algorithm is validated by comparing it with other advanced deep learning algorithms. Using available datasets, the study evaluates the accuracy of the DL system in detecting medical conditions within the Python Jupiter environment. Performance metrics, including F1 score, recall, accuracy, and precision, are used to assess the effectiveness of the proposed RCNN model.

Keywords – Deep Learning, Re-Modelled Convolutional Neural Network (RCNN), Performance Metrics.

I. INTRODUCTION

Cardiovascular disease refers to any major illness that affects the heart. Using machine learning (ML) techniques, researchers are developing smart systems that use electronic health data to correctly identify heart issues [1, 2, 3, 4, 5]. Healthcare service sectors worldwide use ML. Locomotor problems and heart disease prevention are two areas where ML approaches have shown promise in medical data. Researchers' progress provides valuable insights into applying their analysis and determining the best course of action for a specific patient when they uncover such important facts [6]. This should group patients with similar ages and health conditions [7] to assess the reliability of both ML algorithms and their frequency of false negatives.

This uncovered ML approaches in an extensive catalogue of current Internet of Things (IoT) developments across several businesses. There is barely a glimmer of optimism for using ML procedures to forecast heart sickness, according to previous research. Researchers compare and analyse results from the well-known heart disease dataset downloaded from UCI using a change of ML algorithms. Scholars from the "University of California, Irvine" gathered the data, comprising 75 different columns as well as 14 attributes [8]. Python is more reliable and helps monitor and set up many kinds of health-checking apps; therefore, it is ideal for medical care jobs. It offers two components of data processing services: managing categorical variables and converting categorical columns. This describes the main steps of creating an app, which include gathering databases, assessing the properties of the dataset as well as running logistic regression. The random forest (RF) disease classifier algorithm provides a more precise way to detect heart diseases [9].

Existing research uses an optimized adaptive neurofuzzy inference system (ANFIS) along with an artificial bee colony (ABC) to categorize heartbeat sounds. From the cleaned and pre-processed data, it extracts MFCC using the heartbeat sounds. Then evaluate the accuracy by monitoring the pre-handled heartbeat sound using the ABC-ANFIS model [10]. Between 2001 as well as 2021, 270 full-term newborns with difficult CHD underwent a total of 466 scans, including preoperative and postoperative brain MRIs. Over the course of five years, researchers examined clinical variables in relation to white matter damage (WMI), or localized stroke [11]. One research study employed logistic regression for this purpose. An earlier study estimated the prognosis for HF patients using pathophysiological parameters and a correlation matrix to identify characteristics that correspond to the most critical risk factors [12]. The research proposal has made critical contributions to the field.

- Initially, training uses 80% of a heart disease dataset, while testing uses 20%.
- It transforms the dataset before feeding it into the convolutional layers.
- The proposed RCNN model layers are the maxpooling layer (PL), flatten layer (FL), dense layer (DenL) as well as convolutional layer (ConvL).
- The proposed model makes use of the ReLU activation layer and compares it to existing activation functions such as Tanh and Selu.

The reminder of this paper is organised as follows: Section 2 supports the related work on existing techniques in heart disease identification and its demerits. Section 3 covers the proposed enhanced model for heart disease detection based on DL. Section 4 provides information on the two dataset utilised for study and the results. Section 5 presents the brief summary of conclusion and the scope for future improvement.

II. LITERATURE REVIEW

Teixeira et al. [13] used a conventional regression model in conjunction with several ML approaches to develop predictive attrition models. They extensively tested both a model with a constant number of forecasters as well as a model with a changing number of variables provided at each development. K-Nearest Neighbours (KNN), Functional trees, Logistic Regression (LR), Random Forest (RF) along with J48 Consolidated were the five classification techniques used.

Suutari et al. [14] developed the appropriateness model for this unique case study, which included seventeen patients and four family members suffering from heart failure. By annotating field notes from individual interviews, minutes from stakeholders' input and healthcare consultations, it was able to use the experienced-based technique to get details about heart failure along with their treatment. This used reflexive topical assessment to enhance the participants' understanding. White-Williams et al. [15] used both quantitative and qualitative data to illustrate the patient knowledge in an interprofessional collaborative repetition. The Cardiovascular Breakdown Temporary Consideration Administrations for Adults database, comprising 1128 patients, provided the results. This investigation found three noteworthy correlations with patient experience. Between the patient's experience and being single, there was a negative correlation.

Munagala et al. [16] pointed out that a distant checking methodology significantly improves the recognition of inevitable medical care administrations. This uses an Internet of Things (IoT) heart disease detection strategy based on "optimised ensemble learning". It also fine-tunes every classifier's hyperparameter using an enhanced dingo optimiser (I-DOX) method.

Dhande et al. [17] detailed an AI-based method for discovering large features. Finding multi-reason disease expectations is the foundation of their strategy. The prediction model employs various well-known classification methods and variables to generate predictions for diabetes and heart disease. The technique takes an ensemble method to improve the accuracy by employing classification methods as well as feature selection approaches. A voting classifier using AdaBoost and sigmoid decision tree (DT) methods, as well as support vector machines (SVMs), is part of the proposed method. Ninni et al. [18] discussed genotyping blood DNA for cautious aortic valve substitution (AVR) using the Heme PACT board. They used a total of four screening procedures to assess HSM and also studied the outcomes after surgery. Prior to and after surgery, it analyzed a small sample of the patient's blood and heart cells using mass cytometry in conjunction with conventional approaches.

Sonia et al. [19] employed Recursive Feature Elimination (RFE) and other successful feature choosing strategies. Sonia et al. [19] employed various strategies to select pertinent features. Furthermore, performance assessment made use of ML classifiers. This conducted tests on LRs, ANNs, DTs, KNNs [20], and RFs, and compared the outcomes. It combines a number of popular classifiers into one model to solve the classification problems. These include neural networks, KNNs, LR classifiers, DTs, and RFs. It had the best prediction accuracy for LR. Wagner et al. [21] created a network of connections using model-grounded meta-analysis, which included typical dyslexia symptoms such as phonological attentiveness, spoken language along with translating, as well as RTI, family history of dyslexia, and the likelihood of having dyslexia oneself.

III. PROPOSED METHODOLOGY

Finding out the heart illness in patients is challenging as it uses binary classification. Misdiagnosis of a patient's cardiac disease could lead to inappropriate or nonexistent therapy choices. The key goal of this study is to enhance classification approaches, which refer to the precision in identifying a person's cardiac illness.

Inspired by the achievement of deep neural networks, this study proposes a remodeled CNN (RCNN) to circumvent with the problems encountered in existing approaches. **Fig 1** shows the proposed flow used in this study, which consists of two DenL layers, a FL layer, a PL layer, and then two sequential convolution layers with a count of 2. The primary advantage of CNN is the analytical method it offers for directly extracting the raw form properties of input data. Conventional neural networks cannot match CNN's learning and classification capabilities. This used a 1D convolution kernel instead of the usual 2D kernel to leverage the features of the input data. Only after training a 1D-CNN model on the input data it is possible find the predicted value. Starting at the input layer and working its way out to the output layer is the forward propagation process. When forward propagation fails to provide the desired outcomes, Adam's optimizer uses the cross-entropy loss function to control the discrepancy among the actual along with predicted values. Then, Adam's optimizer sends the mistake back to each layer so that it may modify the weight. The network continues to apply new parameters iteratively until it finds the least loss function value.

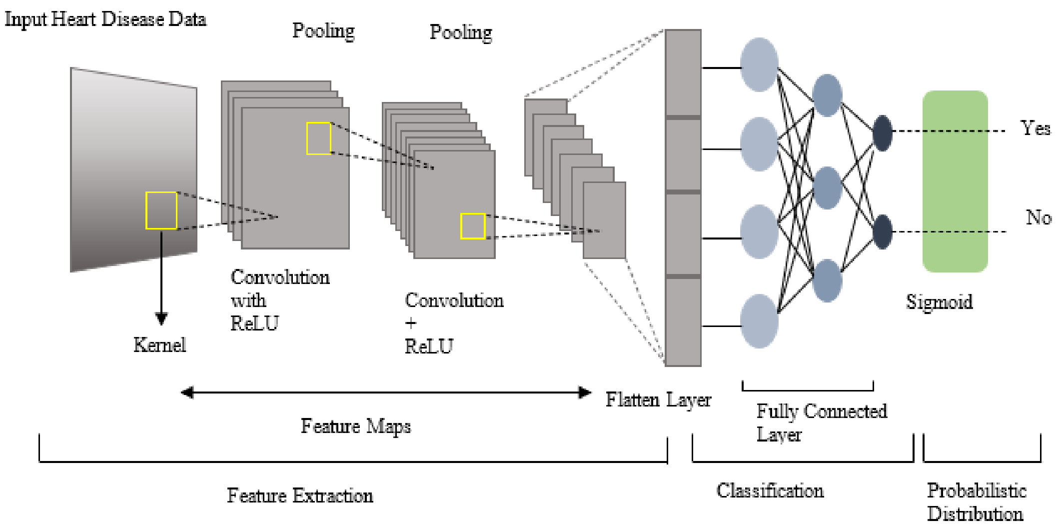


Fig 1. A New Structure for the RCNN Model Layer.

Convolutional Layer

This study retrieved spectral data using a 1D-CNN model. In this work the layer which is used initially is the 1D-CNN layer, depending on the size of the dataset. For local feature extraction, it places the ConvL underneath the sequential layer to work with the dimensionality-reduced feature data.1D-CNN provides the matching feature through its convergence in the local input data area. Every point on the feature map corresponds to a kernel with its own set of characteristics. In order to converge with a smaller number of parameters, 1D-CNNs use weight sharing. This ensures that 1D-CNN will converge quickly as well as efficiently. The kernel size of 3 utilizes all the weights present in both the input and output layers. The kernel window is responsible to assign a weights value to the inputs. To obtain the feature map value, the system combines the input values. Data produced by ConvL serves as input and output to the layer below it. The researchers in this work used two convolutional layers in a sequential fashion.

Pooling Layer

The PL layer, which is employed after the ConvL layer, may extract feature data with lower-resolution, strengthen the network, as well as further decrease the feature vector's dimensionality. CNNs rely on pooling layers. To speed up the next step, PL reductions the number of parameters while charge the significant qualities. So, now we're using the Max approach to analyze all feature maps. For this resolution, it uses the max-PL technique to choose the most severe parameters. This also expect PL techniques to solve the overfitting issue. The PL techniques not only carefully select and direct the maximum values for the subsequent network layer as input to the compressed layer, but also reduce the size of the output values.

Fully Connected Layer

Typically referred to as the DenL, this layer is also termed as the fully connected (FC) layer accepts the data output from the fL layer in order to extract all of the data characteristics. This research employs the ReLU activation function, which improves the network's nonlinear modeling capabilities, helps it understand the network's inspirational data, and ultimately leads to more accurate predictions. Partially responsible for CNN's performance is the FC layer. CNNs analyze each feature independently after dividing the input into a feature vector. The first steps of this level include convolution and pooling. A fully connected final decision is the result of the operation. This can flatten the output of the network's previous phases to create a single vector. Each represents the probability that a class will receive a certain attribute. It takes the feature map and weights to choose the right label. The FC's output layer supplies the ultimate probability for each label. This study examined several activation functions, including Tanh. The output range of the S-shaped Tanh function is -1 to 1. Tanh's output value skews more positively towards 1.0 for larger inputs and more negatively towards -1.0 for smaller ones. Equation (1) provides the tanh mathematical expression.

$$f(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})} \tag{1}$$

Despite having a much larger gradient than the Tanh function, Tanh also has to deal with vanishing gradients. Selu then verifies its activation function. This developed the Scaled Exponential Linear Unit (SELU) to deal with interior normalisation in self-normalising networks. Because of this, the variance along with the mean of every layer remain unchanged. SELU makes this normalisation possible by modifying the mean and variance. The mathematical equation (2) for Selu.

$$f(\alpha, x) = \lambda \begin{cases} \alpha(e^{x} - 1) & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases} \tag{2}$$

There has been little practical use of SELU so far since it is a new activation function. Therefore, the ReLU activation function is used as well as equated (3) for the sake of this study.

$$f(x) = max(0, x) \tag{3}$$

Since this ReLU activation function uses a tiny number of active neurons, it outperforms the other functions in terms of computing efficiency. Adam is an optimization tool. Most academic journals have recently highlighted Adam due to its significantly faster convergence compared to other adaptive methods. Next, it determines the heart disease using the prediction output.

IV. RESULTS AND DISCUSSION

Dataset Description

This study makes use of two datasets [25, 26]. The first dataset characteristics identify individuals with heart failure. The variables include age, smoking time, anaemia, high_blood_pressure, creatinine_phosphokinase, diabetes, DEATH_EVENT, platelets, ejection_fraction, serum_creatinine, serum_sodium as well as sex. The second dataset characteristics identify individuals at high risk of heart illness. The variables include sex, slope, ca, thal, age, trestbps, cp, fbs, exang, chol, oldpeak, restecg, thalach as well as target. **Fig 2** and **Fig 3** shows the visualization of the first dataset and second dataset heatmap.

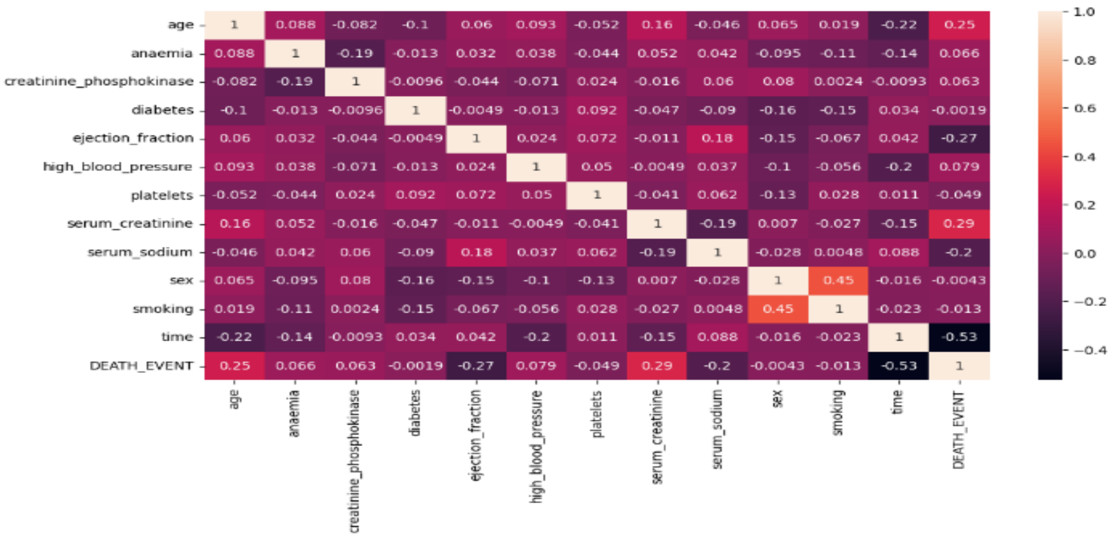


Fig 2. Heart Failure Dataset Heatmap.

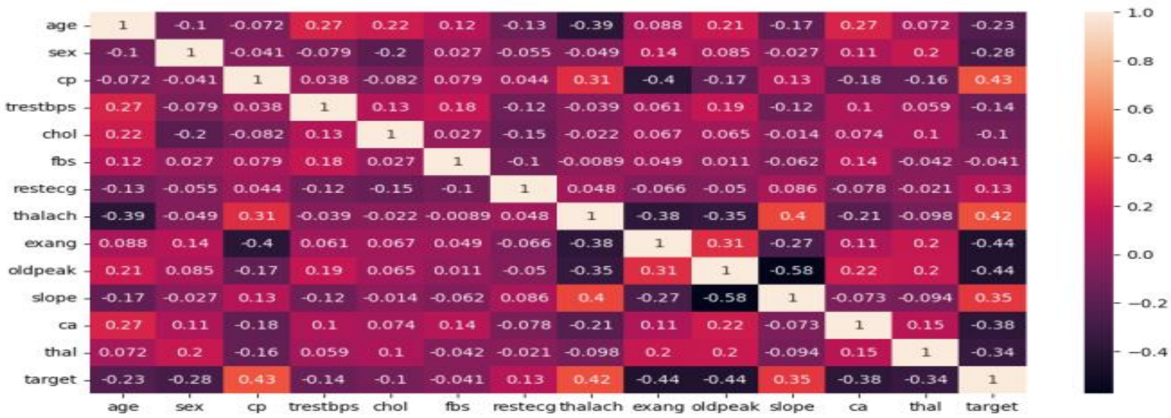


Fig 3. Heatmap for HDD Dataset.

The proposed RCNN model's parameters is detailed in **Table 1**. The initial as well as second layers are the ConvL layers. The PL is the next subsequent layer, and it has a pool size of two. The FL layer comes in at number four. With ten units and the ReLU activation function, the FC makes up the fifth layer. Given the binary classification nature of the proposed research, it uses the sigmoid activation function as the optimal choice for binary classification, making the last layer dense with one unit. Other training parameters include 50 epochs, binary cross-entropy as well as the Adam optimizer.

Table I. The Parameters of The RCNN Model

Layer	Layer Type	Parameter
Maxpooling1D	Pooling	Pool size is 2
Conv1D	Convolutional	32 is the size of the filter, 3 is the size of the kernel, activation is relu, and the dataset size is (13,1).
Dense	Dense	10-unit, activation = relu
Conv1D	Convolutional	The filter size is 16, the kernel size is 3, and the activation is equal to relu.
Flatten	Flatten	-
Dense	Dense	Unit used is 1, and activation is sigmoid

Evaluating the model's performance is necessary for defining the precision with which it would operate with input data. Together, the four pre-existing DL methods and the proposed RCNN model use eight distinct measures to evaluate performance. These measures make it possible to compare several models as well as measure the importance of the data for each label in the classification. Some of the measures include confusion matrix (CM), support, weighted average, f1 score, recall, macro average, accuracy as well as precision. The accuracy measure is the percentage of accepted data relative to all data. The provided data relates to the detection percentage of the inputs. The accuracy equation in (4).

$$\text{accuracy} = \frac{\text{Proper detected data}}{\text{Total data}} \tag{4}$$

The CM's matrix columns display the actual class classifications, while the rows provide the predictions for each class. A complete study makes use of associations such as true positive (TP), false positive (FP), false negative (FN), as well as true negative (TN). The term "TP" means the overall properly identified inputs. Every single class in the matrix has this value on the leading diagonal. When a model gets an input meant for a heart disease patient then again gives it to someone without heart disease, FP predictions without heart disease occur. The term FN refers to a model's inaccurate prediction about a model from a different class. In this case, the input seems like it belongs to a patient with heart disease, then again, the model forecasts that the individual does not really have the disease.

This research uses a metric known as accuracy to assess a model's ability to forecast a certain class. It displays the epochs count in which the model correctly predicted the output for a specific class out of every prediction. As an outcome, this statistic delivers data on the model's accuracy for every class. After adding up TP and FP, divide the total by the TP ratio to get it for every class. Precision corresponds to equation (5).

$$\text{precision} = \frac{\text{TP}}{\text{FP+TP}} \tag{5}$$

Recall is termed as the percentage of samples correctly classified to the overall number of samples in a class. One other name for it is "sensitivity." Equation (6) is considered to be

$$\text{recall} = \frac{\text{TP}}{\text{FN+TP}} \tag{6}$$

The F1 Score represents the harmonic ratio that find the ideal balance between recall and accuracy. Equation (7) contains the formula for an F1 score.

$$\text{F1 score} = 2 * \left(\frac{\text{precision}*\text{recall}}{\text{precision}+\text{recall}}\right) \tag{7}$$

The support data contains the overall frequency for each class. The examination of the dataset's class-wise distribution reveals the number of samples employed in the study. It can summarize all these indicators using both the macro and weighted average approaches. This adds all the classes collected to calculate the overall values of a metrics, comprising F1 score, recall as well as accuracy. Specificity is the of actual negatives proportion that are correctly identified by a classification model. Specificity is expressed as in (8).

$$Specificity = \frac{\mathrm{TN}}{FP+TN} \tag{8}$$

Mean square error (MSE) is also used for performance verification that measures the average squared difference among the actual as well as predicted values. This is illustrated as in (9).

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(y_i - \widehat{y_i})^2 \tag{9}$$

Where n is the data points count, y_i represents the actual value as well as $\widehat{y_i}$ denotes the predicted value.

Comparison

This section compares the proposed RCNN model for heart disease classification with some existing approaches such as ANN, CNN, which uses several activation functions such as Relu, Tanh including Selu. An ANN is meant for the input data transformation over a series of hidden layers, and computes the error at the output layer. The gradient descent method continuously updates the layer weights by retransmitting the error.

Table 2. Comparison of Diverse Existing Models

Methods	Classes	Prec	Rec	F1-score
Heart failure dataset				
ANN	0	0.74	0.92	0.82
	1	079	0.48	0.59
	Acc			0.75
	Macro avg	0.76	0.70	0.71
	Weighted avg	0.76	0.75	0.73
CNN with Tanh	0	0.76	0.95	0.84
	1	0.86	0.52	0.65
	Acc			0.78
	Macro avg	0.81	0.73	0.75
	Weighted avg	0.80	0.78	0.77
CNN with Selu	0	0.77	0.92	0.84
	1	0.81	0.57	0.67
	Acc			0.78
	Macro avg	0.79	0.74	0.75
	Weighted avg	0.79	0.78	0.77
CNN with Relu	0	0.76	0.92	0.83
	1	0.80	0.52	0.63
	Acc			0.77
	Macro avg	0.78	0.72	0.73
	Weighted avg	0.77	0.77	0.75
Proposed RCNN	0	0.84	0.84	0.84
	1	0.74	0.74	0.74
	Acc			0.80
	Macro avg	0.79	0.79	0.79
	Weighted avg	0.80	0.80	0.80
HDD				
ANN	0	0.93	0.86	0.89
	1	0.88	0.94	0.91
	Acc			0.90
	Macro avg	0.91	0.90	0.90
	Weighted avg	0.90	0.90	0.90
CNN with Tanh	0	0.91	0.85	0.88
	1	0.87	0.93	0.90
	Acc			0.89
	Macro avg	0.89	0.89	0.89
	Weighted avg	0.89	0.89	0.89
CNN with Selu	0	0.90	0.88	0.89
	1	0.89	0.91	0.90
	Acc			0.89

	Macro avg	0.89	0.89	0.89
	Weighted avg	0.89	0.89	0.89
CNN with Relu	0	0.95	0.90	0.92
	1	0.91	0.95	0.93
	Acc			0.93
	Macro avg	0.93	0.93	0.93
	Weighted avg	0.93	0.93	0.93
Proposed RCNN	0	0.98	0.90	0.94
	1	0.91	0.98	0.95
	Acc			0.94
	Macro avg	0.95	0.94	0.94
	Weighted avg	0.94	0.94	0.94

For heart failure clinical records dataset class 0 typically refers to patients who did not experience heart failure, while class 1 refers to patients who has heart disease. Models such as CNN with Selu,CNN with Relu , ANN as well as CNN with Tanh perform similarly, with high precision (especially for Class 1) and varying levels of recall. Class 1, which may have fewer instances (i.e., heart failure cases), typically has a lower recall because the models tend to misclassify some heart failure cases as non-cases. The proposed RCNN shows a moderate performance across the board but achieves the best equilibrium among recall along with precision for both classes, with the highest F1-scores for both classes. This suggests that the proposed RCNN model may be better at capturing both non-heart failure (Class 0) cases along with heart failure (Class 1).

For HDD dataset class 0 and class 1 denote diverse status of the HDD (e.g., healthy vs. failing disk). For the HDD dataset, performance is overall high, particularly with the CNN with Relu and proposed RCNN models, which have the highest accuracy, recall, F1-scores as well as precision for both classes. Class 1 (likely HDD failure) has high recall in most models, meaning that the models are very good at identifying failing disks. This is important for predictive maintenance applications where it is crucial to catch failures early. Proposed RCNN consistently performs very well across metrics, with Macro averages and Weighted averages all reaching 0.94-0.95. This suggests the RCNN model is effective at balancing the trade-off between Precision and Recall.

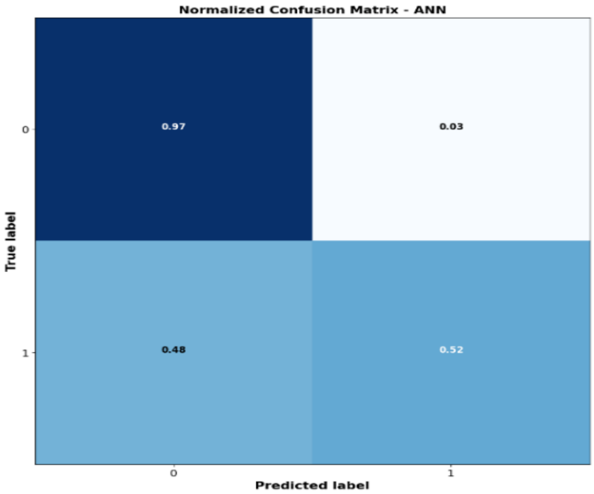
ANN performs reasonably well but has lower precision and recall for Class 1 (heart failure) in the heart failure dataset, which implies it may be less sensitive to predicting heart failure cases. CNN-based models (with Tanh, Selu, and Relu) are very close to each other in performance. These models perform better in terms of Recall along with Precision for Class 0 (healthy patients/HDD healthy disks) but are less effective at Class 1 (heart failure/HDD failures). CNN with Relu shows slightly better results overall, especially for the HDD dataset. The Proposed RCNN stands out, offering the best balance for both classes, especially for the HDD dataset. This suggests it may incorporate more sophisticated methods to enhance performance, likely using a hybrid or specialized CNN architecture.

Table 3. Evaluation of Other Metrics

Methods	Specificity	Mean Squared Error
Heart failure dataset		
ANN	0.91	0.25
CNN with Tanh	0.94	0.21
CNN with Selu	0.91	0.21
CNN with Relu	0.91	0.23
Proposed RCNN	0.83	0.20
HDD		
ANN	0.85	0.09
CNN with Tanh	0.84	0.11
CNN with Selu	0.87	0.10
CNN with Relu	0.89	0.07
Proposed RCNN	0.89	0.05

For the Heart Failure dataset, the Proposed RCNN has the best overall performance, especially in the F1-scores, representing a well-balanced performance across both classes. For the HDD dataset, the proposed RCNN also shows superior performance with very high Accuracy (0.94), demonstrating its effectiveness in predictive tasks like HDD failure prediction. Accuracy is high across most models in both datasets, but the F1-score and the balance between Recall as well as Precision (especially for Class 1) can give a better sense of how well the model handles imbalanced data. Hence, the

Proposed RCNN appears to be the best performing model across both datasets, offering the best balance between Precision and Recall, along with strong overall accuracy. These details are tabulated and pictorially represented in **Table 2** and **Table 3** and in **Fig 4** as well as **Fig 5**.



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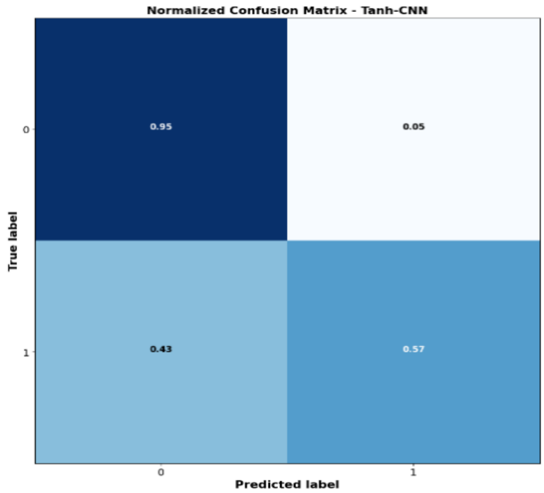

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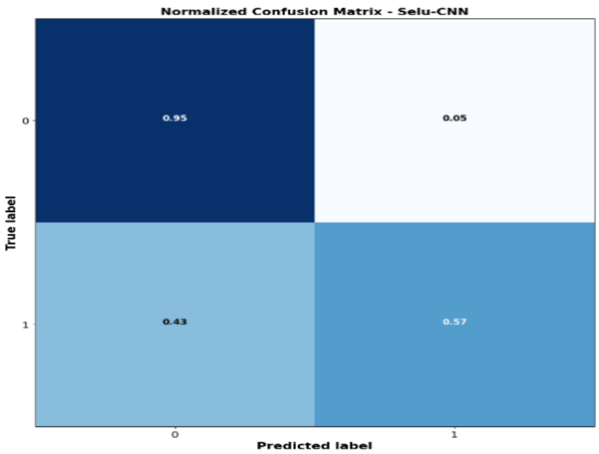

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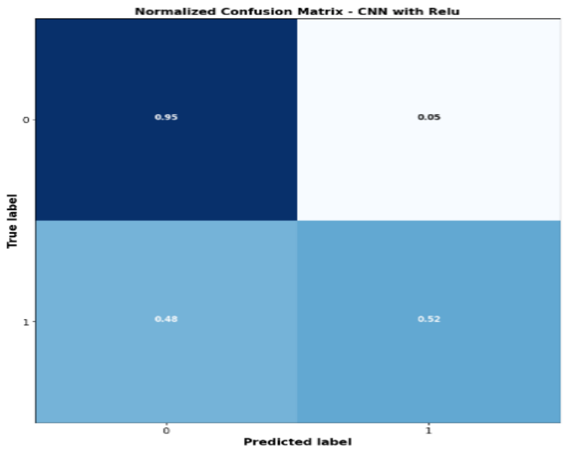

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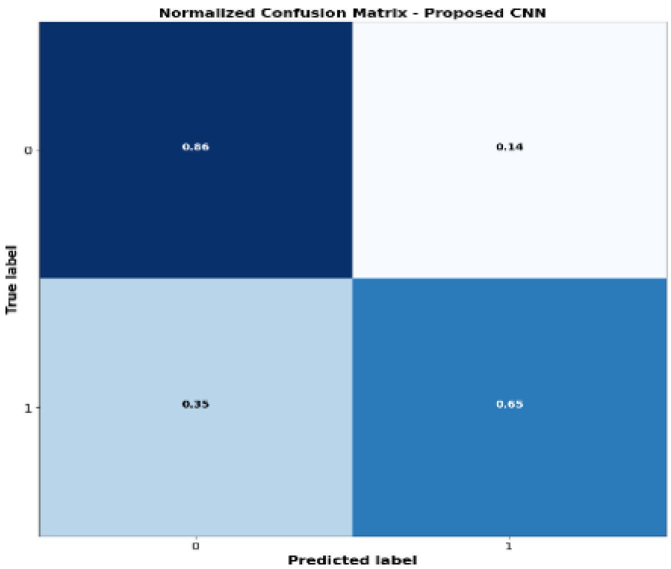
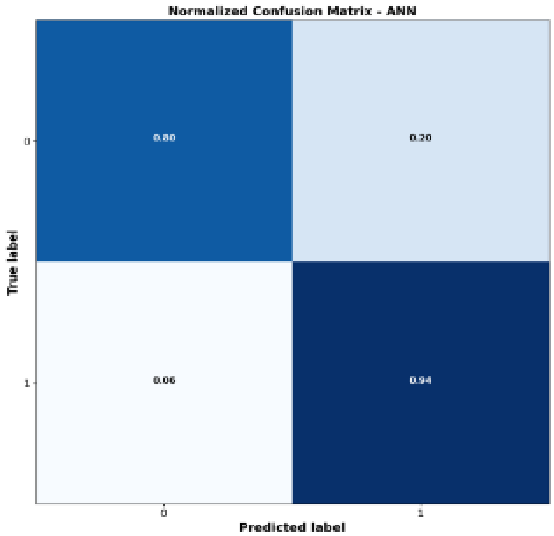


(e)

Fig 4. Heart Failure Clinical Records Dataset Confusion Matrix Representation (A) ANN (B) CNN Using Tanh (C) CNN Using Selu (D) CNN Using Relu (E) Proposed RCNN Model.



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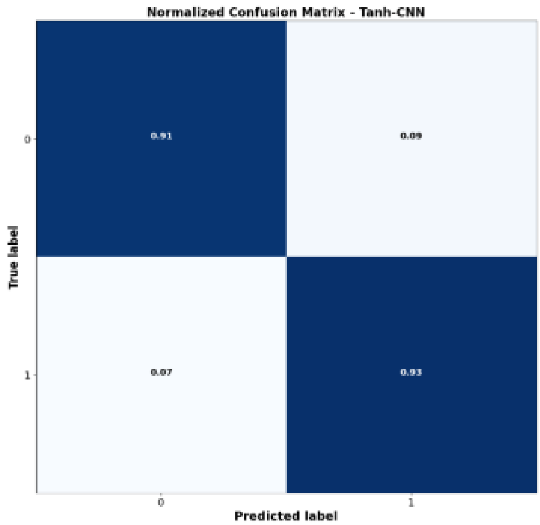

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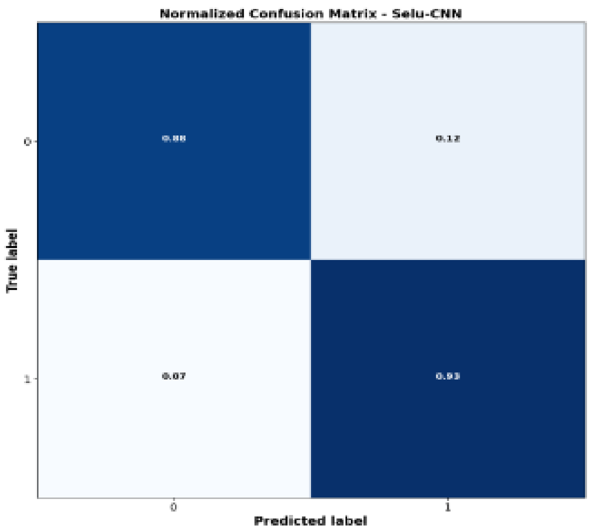

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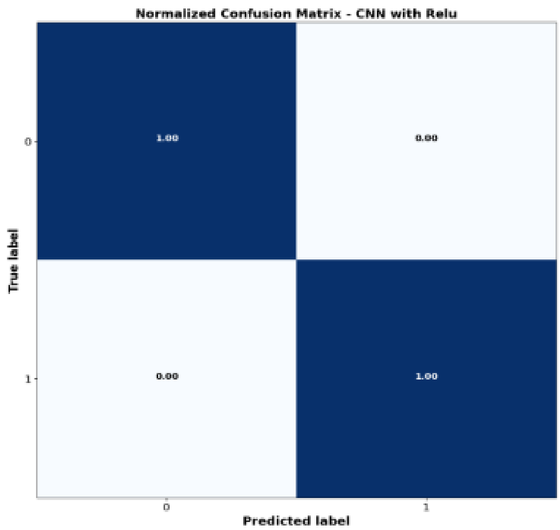

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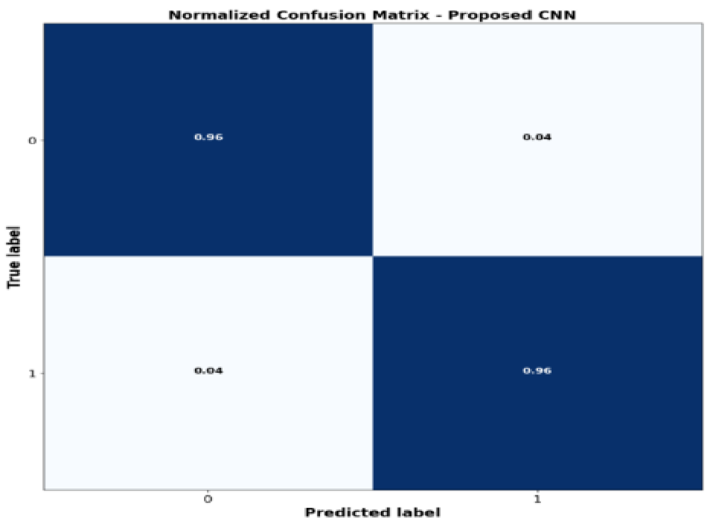

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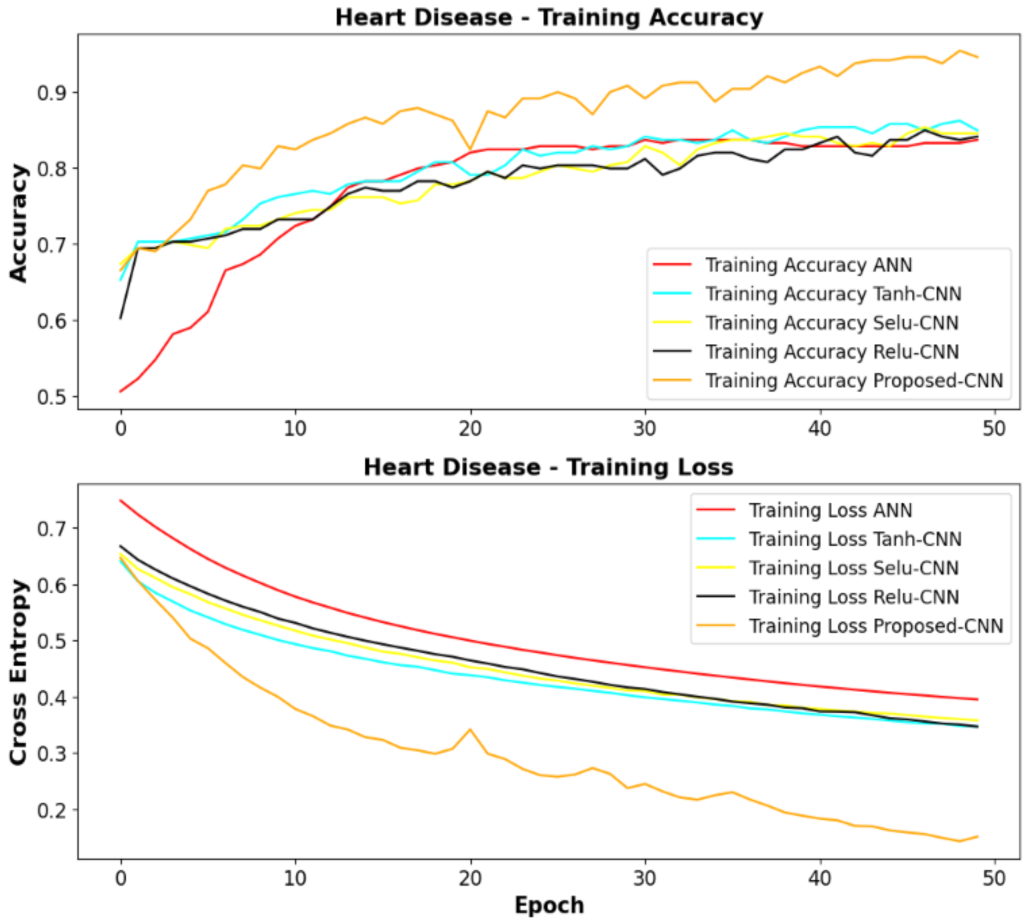
Fig 5. Heart Disease Dataset Confusion Matrix Representation (a) ANN (b) CNN using Tanh (c) CNN using Selu (d) CNN using Relu (e) Proposed RCNN Model.



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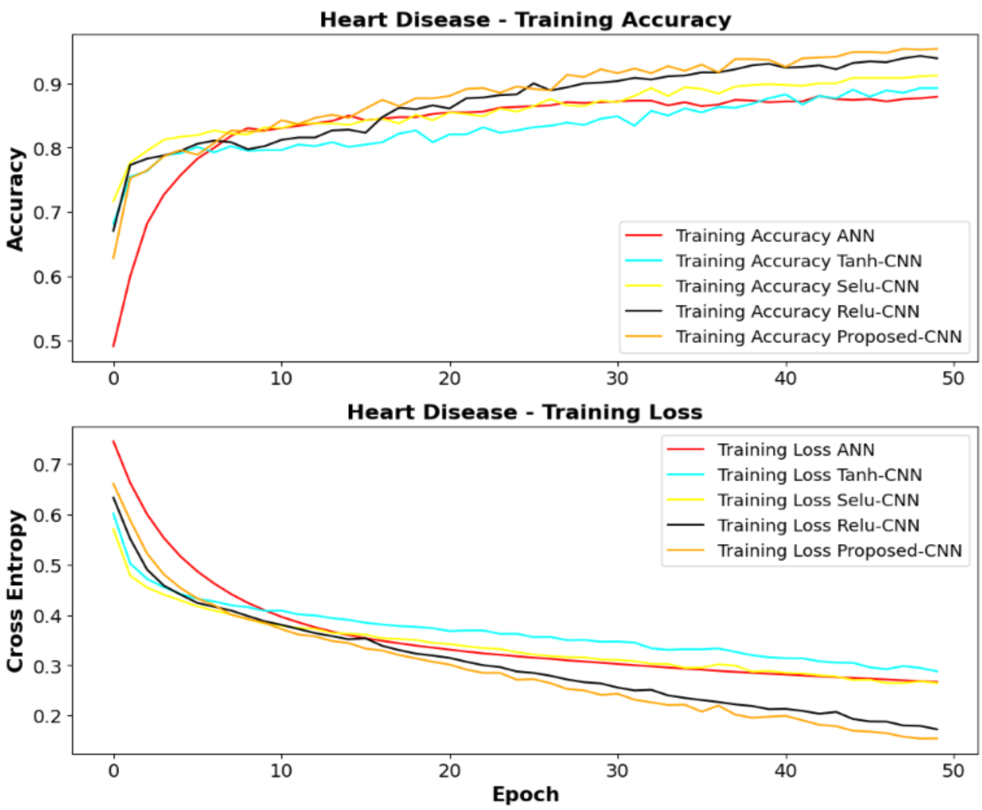

(b)

Fig 6. Training Loss as Well as Accuracy Comparison Graph (a) Heart Failure Dataset (b) HDD Dataset.

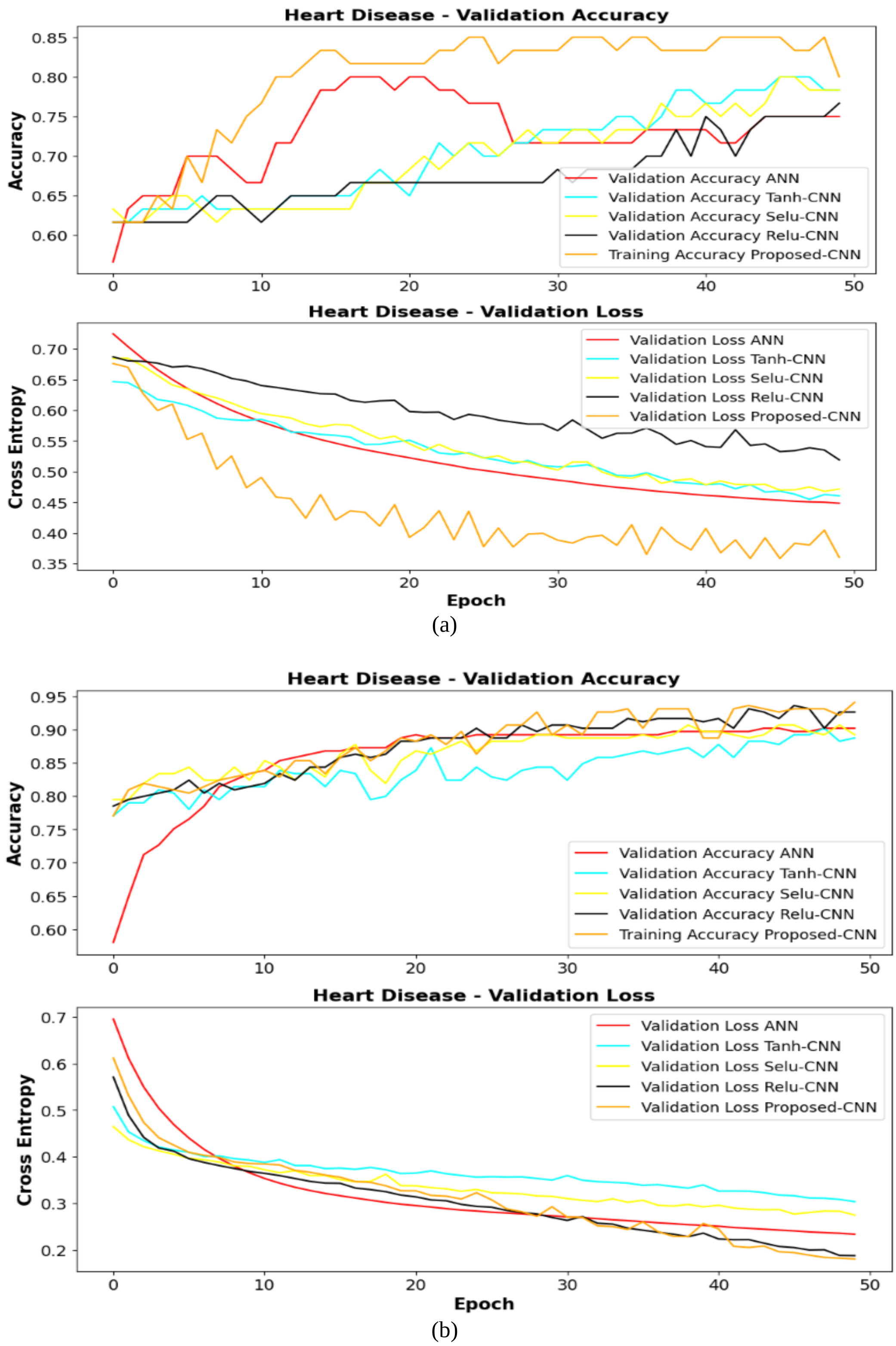

Fig 7. Validation Loss as Well as Accuracy Comparison Graph (a) Heart Failure Dataset (b) HDD Dataset**.**

Fig 6 shows the training loss along with training accuracy improvement graphs. **Fig 7** explains the validation loss as well as validation accuracy improvement graph. The orange line in the figures represents the proposed RCNN model. The proposed RCNN model achieves improved results than its predecessors in terms of both losses along with accuracy. For the detection of cardiac disease, the proposed RCNN model performs better than other existing approaches. Although the proposed work has better heart disease predicted accuracy up to this point, there are still limits. This study employs DL algorithms alongside ML techniques for the efficient heart disease detection. Therefore, employing a mix of ML as well as DL algorithms may expand this work, provided that DL methods exhibit certain accuracy issues.

V. CONCLUSION

In this investigation, it designs the RCNN model to detect cardiac illness. It tests the proposed model's effectiveness against existing DL approaches to conduct a comparative evaluation as well as attain true positive performance. The results of this investigation show that the proposed RCNN model is more effective than statistical approaches. This study presents the results of some research studies that demonstrate the effectiveness of this model in predicting and diagnosing cardiac disease. This evaluates the performance parameters of every recently published DL classification model, including recall, F1 score, accuracy, precision as well as others, using available data set. The goal of the next study is to enhance the algorithm even further by integrating DL and machine learning methods.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: Mohammad Azhar and Mary Gladence L; **Methodology:** Mohammad Azhar; **Software:** Mary Gladence L; **Writing- Original Draft Preparation:** Mohammad Azhar and Mary Gladence L; **Validation:** Mary Gladence L; **Writing- Reviewing and Editing:** Mohammad Azhar and Mary Gladence L; All authors reviewed the results and approved the final version of the manuscript.

Data Availability

The Datasets used and /or analysed during the current study available from the corresponding author on reasonable request.

Conflicts of Interests

The authors declare no conflicts of interest(s).

Funding

No fundings.

Competing Interests

There are no competing interests.

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