Early Detection of Cardiovascular Diseases using Deep Learning Feature Fusion and MRI Image Analysis

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Abstract

Deaths from cardiovascular disease (CVD) are more common than any other kind of mortality in the world. Electrocardiograms, two-dimensional echocardiograms, and stress tests are only a few of the diagnostic tools available to combat the rising incidence of cardiovascular disease. Since the electrocardiogram (ECG) is a clinical therapeutic agent that does not need any intrusive procedures, it may be used to diagnose cardiovascular disease (CVD) early and prescribe the appropriate treatment to prevent its fatal consequences. However, it may be time-consuming and demanding for a physical examination to interpret all these signals from various pieces of equipment, especially if they are non-stationary and repeating. It is necessary to use a computer-assisted model for rapid and precise prediction of CVDs since the Heart Signal from an ECG machine is not a stationary sign, the differences may not be repeated and may manifest at different intervals. In this paper, we offer a fully deep convolutional neural network-based automated diagnosis technique for cardiovascular illness. In order to extract those form characteristics from the Kaggle cardio-vascular disease dataset, CVD-MRI is employed in this detection method. In this case, the risk of cardiovascular disease is estimated using a completely deep convolution neural network and deep learning convolution filters (CVD). The suggested operation's main goal is to "improve the accuracy of completely deep convolution neural network while simultaneously reducing the complexity of the computation and the cost function." Accuracy of 88 percent is achieved by the proposed fully deep convolutional neural network.

Keywords: Cardiovascular Disease; Deep Learning Fusion; MRI Image; Model Fusion

1. Introduction

Heart disease in humans has become a big issue in modern society. The human heart is a vital organ that distributes blood throughout the body through the circulatory system [1]. Besides expelling carbon dioxide and other pollutants, the circulatory system is responsible for transporting oxygen and nutrients throughout the body.

Because recent research found that 86% of the world's population is affected by CVD, the issue has risen to international prominence. In India, the prevalence of CVD is much higher, affecting 89% of the people. Statistics show that over 75% of people here are uncomfortable bringing up the stressors in their lives and the financial burden of discussing them with a healthcare provider. That's why experts are now particularly interested in studying CVD and its therapy. Heart disease (CVD) [2], [3]may be diagnosed in two ways: surgically (invasive) and non-surgically (non-invasive)[4], [5]. Images captured using catheters fall under the category of invasive approaches[6], [7], whereas those captured using other methods are classified as non-invasive image models[8], [9]. To refine the state-of-the-art in ML and AI-based diagnosis in the present day[10]–[14]. There is a major

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impact of ML and AI on healthcare. The ML performance approach efficiently and proficiently eliminates data from photos and denotes data[15]–[17].

Internal and environmental factors (such as work-related stress, interpersonal conflict, pollution, chemical and physical environments, poor working conditions, and sickness) may all contribute to chronic disease (CVD). In certain cases of CVD, the victim has been put in an unusual position in which he or she has no precedent and has a hard time coping with the accompanying feelings of worry and panic. Commonly, CVD strikes when a person's current physiological and physical resources and skills are insufficient to meet their needs.

Besides an elevated heart rate (Heart Rate Variability), particular breathing rate, galvanic skin, an extended under-study, tense muscles, etc. [18], there are additional physiological aspects. It was formerly thought that the autonomic nervous system (ANS) would respond physiologically to CVD. Cardiovascular disease (CVD) that persists over time would upset the normal proportions of sympathetic and parasympathetic components of the autonomic nervous system (ANS). There is a possibility that the sympathetic system will be overactivated at the expense of the parasympathetic system. Medical devices often determine heart function by analyzing electrical impulses called electrocardiograms, thus any alterations to this data must be communicated to the heart (ECG). Thus, the ECG data signal is significantly facilitated internationally as a legitimate and trustworthy input signal for the assessment of CVD of people.

For the most part, the convolutional layer in artificial neural networks (ANNs) remains buried, but DNNs are breaking new ground by bringing it to the forefront. In the last decade, the concepts of DNN have been applied in many areas, such as the implementation of computer vision tasks in a new domain, signal detection for motion recognition using techniques like electromyogram (EMG) and electroencephalogram (EEG) pattern analysis, and the control of automated assistance devices.

DNN was very helpful in classifying ECG indices for purposes such as detecting arrhythmias, determining the constituents of a signal, performing biometric recognition, etc. These results pointed to DNN's ability to detect stress in ECG and led to its effectiveness in identifying biosignals. DNN's key benefit is that it can automatically and swiftly extract knowledge from massive data by extracting the features on its own via the hidden layer of the given job. Since this was not a concern for us, we did not employ DNN for CVD diagnosis and instead relied on HRV evaluations of ECG data. To the best of the author's knowledge, the accuracy setting can help get in this experimental investigation may be the first of its kind to predict the CVD level by analyzing an ECG signal recorded in mat format and classifying it into three levels: cardiac arrhythmia (ARR), heart failure (CHF), and normal sinus rhythm (NSR). Figure 1 shows the steps of the proposed model.

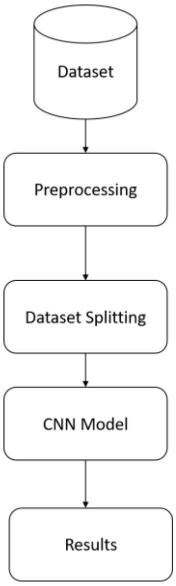

Figure 1: The proposed Model

Below is a review of the most contribution of this study:

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A. In this publication, we proposed a deep learning-based completely deep convolutional network for the diagnosis of cardiovascular disorders.
B. The Kaggle cardio-vascular illness dataset serves as the basis for the first input data.
C. Deep convolutional filters are used for pre-processing
D. The suggested pixel-wise segmentation approach is used to segment the Region of Interest (ROI).
E. Next, a completely deep convolutional network is used to extract the features.
F. Evaluation metrics such as accuracy, sensitivity, specificity, F-Measure, Recall, MCC analysis, Left Ventricle (LV), Right Ventricle (RV), Ejection Fraction analysis, Myocardial Mass, Wall Thickness, Edges analysis, corners, Scale Invariant Feature Transform (SIFT), Speeded up Robust Feature (SURF) analysis, Left Atrium, Right Atrium, and Coronary Arteries analysis are used to assess the
G. Then, we use statistical measures to compare and contrast the various evaluation metrics utilizing known methods like Random Forest Classifier with principal component analysis and Dice metric to investigate the performance

This is how the rest of the document will be structured. In Section 2, we detail our study's approach, including our use of a DNN architecture, our choice of data, and our preparation for the experiments. Results from the tests are discussed in Section 3, and our analysis is wrapped up in Conclusions.

2. Literature Survey

In this part, we evaluated a subset of the many ongoing research activities aimed at detecting cardiovascular disease using a variety of learning classifiers.
Machine learning has been used to automatically diagnose DCM and ASD disorders, as demonstrated by Borkar et al. [18]. Images were processed to extract features, and those features were then categorized using a supervised support vector machine technique. The given approach aimed to evaluate how far state-of-the-art deep learning models can predict CMR segmenting of the myocardium and the two ventricles for categorizing diseases. In addition, this technique plays a significant role in LV identification by discarding multilayered feature maps. Detection of the LV zone with high accuracy and performance required an autonomous and resilient method.

P. Madhan Mohan et al. [19] use pulse rate variance data to assess CVD severity. The optical Photoplethysmography (PPG) sensor was used for HRV forecasting. High, low, and extremely low heart rates were identified as distinct categories.

According to Jie Zhang et al. [20], the parameter Heart Rate was utilized to determine the severity of CVD. The RR interval is determined by analyzing an ECG signal (ECG). The actual positive and negative rates were used to calculate the RR values. With both positive and negative evaluations, the SVM classification model is applied. The severity of CVD may be estimated by disentangling these two rules. Multiple iterations were performed using the SBS method.

Using electrocardiographs in a variety of settings and climates to identify CVD using physiological data was suggested by Monika Chauhan et al. [21]. SVM, Decision Tree, linear discriminant analysis (LDA), and ANN classification methods are used inside the framework to classify a person's typical state and stress levels.

In order to identify cardiac diseases, Ghiasi et al. [22] provide a non-linear analysis of heart sounds that incorporates a quantitative assessment of recurrence. Here, cardiac echo recordings from Physio Net/Computing on Cardiology were processed using a feature removal and arranging strategy that improved the ability to distinguish between two typical categories of cardiac arrhythmias: mitral valve prolapsed (MVP) and coronary artery disease (CAD). All of the available algorithms for cardiac segmentation are compared and contrasted in this procedure, and the most effective and precise method is then suggested. However, in the current state of the art, the solution does not presuppose segmentation of the tip and base.

Patients with cardiac amyloidosis (CA) may be identified with the presence of left ventricular hypertrophy and a poor prognosis, as proposed by Cariou et al. [23]. Several cardiac conditions,

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such as aortic stenosis, hypertension, hypertrophic cardiomyopathy (HCM), and cardiac amyloidosis, have been linked to an increased maximal thickness of the left ventricular myocardium on echocardiography (CA). The volume of the left ventricle (LV) myocardium is precisely measured using this method throughout many heartbeats. Metrics like the Hausdorff distance and the DSC metrics of the contours demonstrate the great accuracy of the solution. The issues of fading gradients and overfitting were not addressed by the remedy.

Automatic phonocardiogram (PCG) signal-based identification of cardiac valve disease was provided by Tuncer et al. [24]. For this work, we employ a graph-based strategy called the Petersen graph pattern to generate novel graph-based features (PGP). By fusing TEP and PGP, we were able to construct an innovative network for generating features at several levels. However, cutoff regression does not get rid of local excessive noise and intensity homogeneity impacts. However, lacking border information might also cause problems with segmentation in the nearby region.

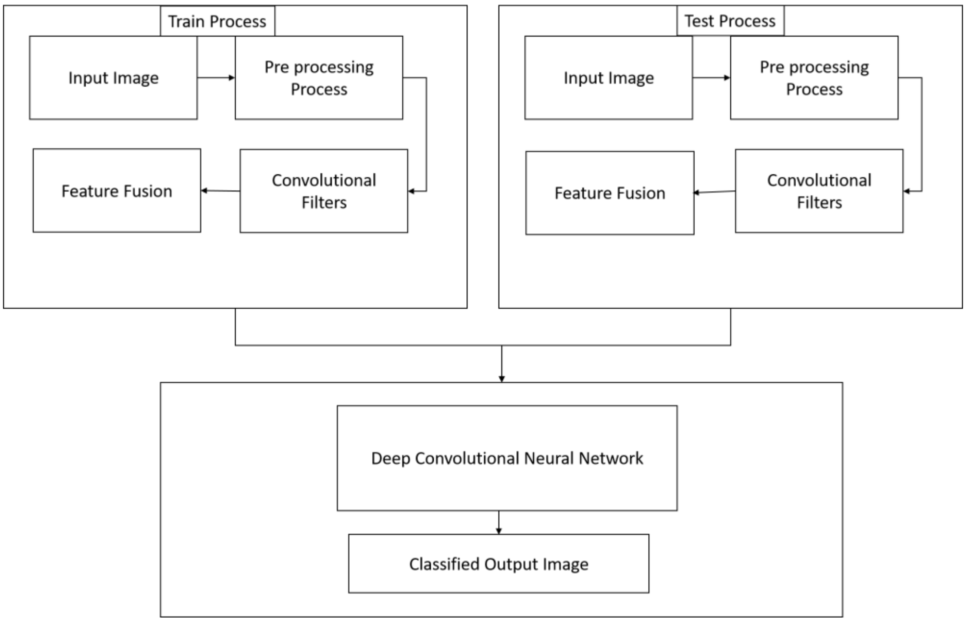

Figure 2: CAD Diagram

3. Research Method

The methods we used to study the challenge of detecting CVD using ECG signals will be discussed in this part. The DNN Classifier was fed data from the ECG data.mat file. All of the data in ECGData.mat has been tweaked from their original versions.

Detecting cardiovascular illness from an MRI picture using a completely deep convolutional neural network is described. The cardiovascular disease detection block diagram is shown in Fig. 1. To begin, cardiac MRI scans are extracted as input from a variety of datasets.

Because of the high levels of noise in the input picture, it is sent to the preprocessing step, where deep convolutional filters are used to clean it up. After being cleaned up, the picture goes through segmentation, where the suggested pixel-wise segmentation approach is used to separate the region of interest (ROI), which is then rearranged into its original dimensions and shapes.

After the picture has been segmented, it is moved on to the feature extraction phase, where the image characteristics are characterized and identified by employing the suggested completely deep convolutional network. Figure 2 shows the CAD diagram.

3.1 Feature Selection

Selecting features for multi-class data is difficult. Existing feature selection methods often only apply to data with a single categorical label. To narrow down a vast feature collection to a manageable quantity, we offer a novel technique based on the well-known area under the ROC

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curve (AUC). In the context of binary classification issues, AUC is a common measure of performance. Hassan et al. introduced and developed a unique method called multi-class AUC for calculating AUC scores in multi-class issues. Here, we use multi-class AUC to determine which attributes are most useful for determining how to categorize the data. Here, we assume a multi-class issue as an example to briefly discuss the multi-class AUC.

3.2 Feature Fusion

This new dataset, comprised of both hand-picked and artificially-enhanced attributes, might be used to train a classifier. In this research, the decision tree classifier was utilized because of its simplicity, widespread usage, and high efficiency. We chose the decision tree over other popular classifiers like SVMs and CNNs because their success does not rely on picking the right parameters.

3.3 Image Acquisition

The data used in this experiment come from the Kaggle cardiovascular illness dataset. It has 60,000 patient records with 12 characteristics. In this study, we use 40,000 MRI images for training and 20,00 for testing, out of a total of 60,000 MRI images.

3.4 Pre-processing

The pre-processing phase is covered here. In this case, the high intensity of the input MRI picture causes harm owing to bias fields. This means that the original MRI picture is very noisy and has poor contrast inside the study area (ROI). Deep convolutional filters are employed in the pre-processing stage to improve picture quality.

3.5 Complex convolutional filters

To restore picture quality and reduce noise, MRI input images are often filtered using deep convolutional filters. Through the use of a deep convolutional filter, a blurry input picture may be transformed into a high-quality one. Using this method, it is possible to lessen the amount of background noise in the original picture. The suggested deep convolutional filter's de-noising equation is then.

For CVD prediction, three well-known supervised ML techniques were applied during model training. The RPMs were trained and tested using artificial neural networks (ANNs), support vector machines (SVMs), and decision trees (DTs). The models were trained using different permutations of the specified methods. To find the most effective ML models, we experimented with different hyperparameter settings and setups, so we could utilize Cohen's Kappa-statistic as a preliminary filter before committing to more conventional performance matrices. This measurement is used to evaluate how well the observed data fit the estimated model. The greater the coefficient (0.60) the better the prediction model. Early on, we narrowed down the pool of potential ML models to just those that exhibited moderate to a large agreement among estimated and observed models using the Kappa-statistic (k) close to 0.60 or 0.60. k-value cutoffs may be set arbitrarily. The choice of a threshold, however, is context-specific [23]. These delicate issues call for a greater weighting of (k). The onset of cardiovascular disease or death from any cause was the primary outcome of this research. Therefore, some degree of consensus amongst models was essential. Using this metric, we settled on the optimal hyperparameters for four ML models: an ANN with a hidden layer, a support vector machine (SVM) with linear and RBF kernel functions kernels using serial minimum optimization (SMO), and a random forest (RF). This section provides the completed schemes for these four Ml algorithms together with associated hyperparameters.

Single-hidden-layer ANN model with sigmoid activation function and 8-node hidden layer. In the end, we settled on a multilayer-perceptron (MLP) trained using the backpropagation technique with a momentum and learning rate of 0.3. We also employed weight decay, a regularisation approach, to prevent over-fitting.

Linear kernel support vector machine (SVM) model: The SVM was fed the complete dataset and primarily trained using two kernels, a linear kernel, and an RBF kernel. To simulate the binary result, these kernels looked for ideal hyperplanes by identifying correlations between features in the dataset. Linear kernel SVM, on the other hand, did well in both the development/certification procedures. When developing this SVM model, the SMO technique was used to optimize it. While

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experimenting with several values for the cost function (ct) to optimize the linear SVM model, we found that ct = 0.5 yielded the best RPM.

To get a feel for any potential non-linear trends in the data, we also evaluated the radial base function SVM (RBF-SVM) model. RBF-primary SVM's parameters, ct and gamma, required fine-tuning. As a result, the model was optimized using a range of cost function values (ct), with 1.0 and 0.01% gamma yielding the best RPM.

We have employed many different varieties of DT, including C4.5, J48, and the RF model. However, the RF fared well among these decision trees and was subjected to further testing so that risk prediction models could be developed. Multiple DTs were generated from a collection of features picked using without the substitution approach, and the RF ensemble method was employed to do so. Cases and controls were separated into groups with comparable characteristics using these DTs. The results of the features were forecasted using the voting procedure. We were able to get a slightly better RPM by using 300 DT at a level of 6 and 3 chosen at random features.

4. Discussion and Results

Here, we take a look at the experimental outcomes of the proposed fully deep convolutional network for cardiovascular disease detection and discuss the implications of these findings. The simulations are run on a Windows 10 PC. Tensorflow is used to do simulations of the suggested procedure. Metrics for success are examined here. Finally, we compare the proposed fully deep convolutional network for identifying cardiovascular illness to state-of-the-art algorithms like Random Forest Classifier with principle component analysis.

4.1 Description of Dataset

The data used in this study come from Kaggle's cardiovascular illness dataset. It has 60,000 patient records with 12 characteristics. In this experiment, we use 40,000 data for training and 20,000 data for testing out of a total of 60,000 data.

Filtering and refining the raw ECG signals is necessary before doing a study of the HRV rate. Therefore, we identified the R- Peak wavelength for the ECG signal inside each window, and a careful analysis was carried out to fine-tune the phony approval and phony denial of the R peak, to eliminate distortion of ECG signals. Then, parameters were used to remove all irrational inter-mission between RRs. It was the normal-to-normal (NN) interval that was utilized to generate the binary pattern, where the locations of the R peaks were represented by the value 1 and the remainder by the value 0.

In our suggested DNN Model, we used a total of four layers. Flattened wavelet ECG signals were used for the first layer. Two ReLU layers followed, and then a softmax layer. Former research only used the partition in the testing set once, but the training procedure was performed four times. The average accuracy and precision of the four folds were utilized to further increase accuracy. We obtain accuracy reach to 88%.

As shown by the comparison of our suggested algorithm's performance with that of other ML algorithms on the prediction of shear strength identification on the MIT-BIH dataset, our method has shown to be more successful than its competitors. Table 1 below summarises the results of several different accuracy tests applied to popular algorithms, and figure 3 plots these results graphically.

Table 1: Results of ML algorithms.

Algorithm	Accuracy
SVM	70%
KNN	75%
Random Forest	80%
Proposed Model	88%

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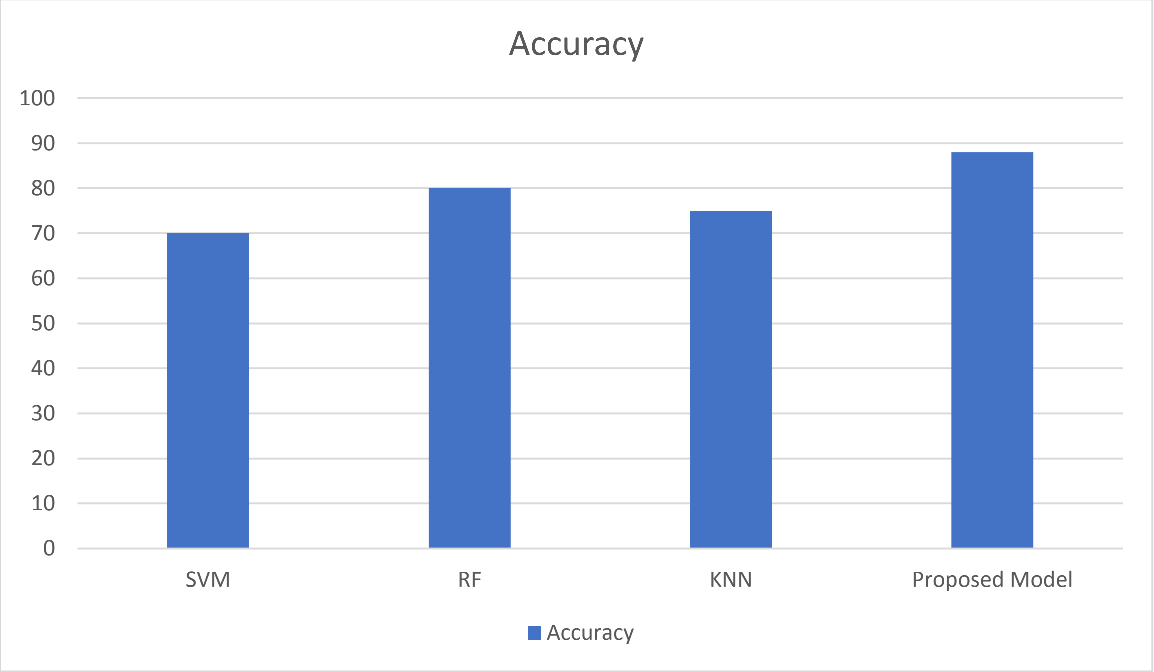

Figure 3: The accuracy of the proposed Model.

The finished baseline RPM has 14 capabilities, and ML-based Engine speed employs the same 14 characteristics (1). Four models were selected for further processing after an initial test of Machine learning using the Kappa-statistic. Table 2 displays the results of an evaluation of completed ML models. RPMs with an accuracy of 81.09% and an AUC of 0.871 were generated using the first completed model (an ANN with a single hidden layer). The ANN-based model consistently predicted the true positive (TP) and true negative (TN) values of the dataset, with a sensitivity of 0.780 and a specificity of 0.848. The best hyperplanes were provided by the linear SVM, which had an accuracy of 80.86%. In addition, the two ML models enhance classification accuracy above the gold standard by 3.7% and 2.7%, respectively. Positive NRI values show that participants are reclassified into a better risk category by these two Ml algorithms compared to the baseline model. RBF-SVM and RF are the other two variants available. Similarities in RBF-SVM scores suggest that certain aspects of the dataset may interact with one another. Among the four chosen ML models, ANN has the highest performance matrices. For sensitivity, the RF model performed well. But its other matrices did not outperform those of competing ML-based RPMs. Table 2 shows that the relative importance of RPMs' performances varies among performance metrics, particularly concerning AUC and RMSE. Following the "No Free Lunch Theorem," however, there is no one ideal optimization method, hence it is not necessary to have better results for a specific approach on all performance measurements. The implication is that there is no optimal ML strategy for predictive modeling tasks. As a result, the most effective algorithm is the one that satisfies the vast majority of performance metrics. Additionally, a table with the outcomes of a five-fold cross-validation experiment has been included for your convenience. Both 5- and 10-fold bridges produced the same results.

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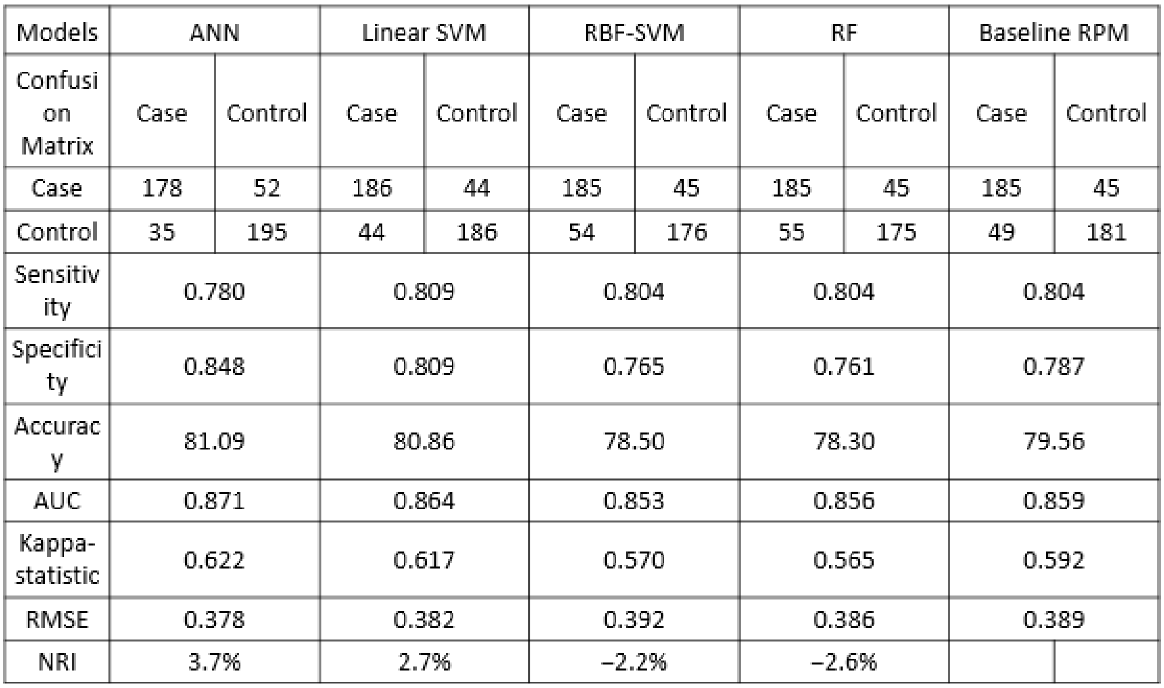
Table 2: The ML methods accuracy.



Models	ANN		Linear SVM		RBF-SVM		RF		Baseline RPM	
Confusion Matrix	Case	Control	Case	Control	Case	Control	Case	Control	Case	Control
Case	178	52	186	44	185	45	185	45	185	45
Control	35	195	44	186	54	176	55	175	49	181
Sensitivity	0.780		0.809		0.804		0.804		0.804	
Specificity	0.848		0.809		0.765		0.761		0.787	
Accuracy	81.09		80.86		78.50		78.30		79.56	
AUC	0.871		0.864		0.853		0.856		0.859	
Kappa-statistic	0.622		0.617		0.570		0.565		0.592	
RMSE	0.378		0.382		0.392		0.386		0.389	
NRI	3.7%		2.7%		−2.2%		−2.6%			

Most performance matrices, except for sensitivity, favor RPMs based on artificial neural networks and linear support vector machines over those based on machine learning and the baseline. Five and 6 of the six requirements were met by these two models, respectively. It was found that the RMSE for the RF model was somewhat better. As a whole, RPMs built on ANN and quadratic SVM fared better than those built on RBF-SVM, RF, and the baseline. As a result, when compared to the traditional baseline RPM, these two alternatives demonstrated their worth as viable options for early threat assessment of CVDs. It was observed that linear SVM-based RPM was so much more reliable than ANN- and LRA-based RPMs and met all performance requirements. The linear support vector machine's (SVM) supplied weights may be utilized for future readings and forecasts, making the process easier for end users.

5. Conclusion

This paper presents an automated technique for identifying heart disease using MRI that relies on a fully deep convolutional neural network. The input picture, in this case, comes from Kaggle's cardiovascular illness dataset. After that, the proposed DL system uses computational complexity and cost function. The experimental results suggest that the proposed detection model has superior performance, reaching an accuracy of 88%. We were able to determine which morphological attributes are most useful for the prediction of attitude stress by using the ECG peaks as an input vector to the DNN. Through the use of a DNN, we were able to collect a comprehensive model for differentiating the ECG signal to detect a specific kind of cardiovascular disease.

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