International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Cardiac Abnormalities Classification Model Using Improved Deep Learning Approach

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Submitted: 26/08/2023 **Revised:** 15/10/2023 **Accepted:** 27/10/2023

Abstract: Worldwide, deep learning (DL) is applied in the healthcare industry. In the medical data set, DL approaches aid in the prevention of cardiac illnesses and locomotor disorders. The finding of such crucial information gives researchers important new knowledge on how to apply their diagnosis as well as therapy to a specific patient. Researchers analyze vast quantities of intricate healthcare data using a variety of DL techniques, which enable medical experts to forecast disorders. The primary motivation for developing a model that identify cardiac disorders, which will help lots of people around the world. This paper offerings a model for detecting cardiac diseases. The model is made by improving the Convolutional Neural Network (CNN) termed as Custom CNN (C-CNN). The new results depict that the proposed model works better. The proposed measure of heart disease categorization performs better when compared to certain previously published approaches.

Keywords: *Deep learning, cardiac, Convolutional Neural Network, accuracy, classification.*

1. Introduction

Cardiovascular diseases are the chief cause of death globally, killing 17.9 lot people all year. Since there are several categories of cardiac disorders, such as bradycardia and atrial fibrillation, diverse issues need different therapy [1]. Using these datasets, a team created a CNN technique to identify arrhythmias. Electrocardiograms (ECGs) from a brand-new group of patients who weren't in the training dataset were collected for the test dataset. A group of board-certified, working cardiologists glossed over the test dataset after reaching consensus [2].

Before being analyzed or developed, the majority of 12-lead ECG classification studies train on a single, small, or homogeneous dataset. Furthermore, greatest algorithms [3] focus on a minor group of cardiac arrhythmias, which does not adequately represent the difficulty as well as complexity of ECG interpretation. However, this is the first study to see whether deep CNN models can notice COVID-19 in ECG trace images. COVID-19 along with other Cardio Vascular Diseases (CVDs) were discovered in research by means of deep learning methods [4].

The ECG is a greatest frequently utilized analytic tools in healthcare as well as medicine. Deep learning systems have shown encouraging results on tasks involving predictive ECG as well as healthcare data. Here, equally modeling as well as application perspectives on deep learning means for ECG data are thoroughly explored [5]. A 98% accuracy rate was employed in the research to determine the four primary cardiac anomalies (irregular heartbeat, previous history of MI, myocardial infarction as well as normal class) [6].

The use of machine learning (ML) techniques to enhance image acquisition, quantification, and segmentation enhances the assessment of fetal cardiac function. It also supports the prenatal diagnosis of fetal cardiac remodeling and abnormalities, which is briefly discussed here [7]. For these tasks, two deep learning approaches are used: Long Short-Term Memory (LSTM), which is based on a recurrent neural network (RNN), and Variational Auto Encoder (VAE), which is based on an autoencoder [8]. The respite of the paper organization is given below. Section 2 evaluations existing researches related to cardiac disease detection. The proposed C-CNN is detailed in section 3 and its results conversation is made in section 4. Section 5 completes the work tracked by the references.

2. Literature Review

Some of the recent related methods related to cardiac disease prediction is reviewed in this section.

For this investigation, Ramesh et al. [9] used a 303-row, 76-property online UCI dataset. It is necessary to evaluate a total of 14 of these 76 properties in order to verify how well

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different approaches work. Utilizing the measurements and attributes that are crucial to data collection, the isolation forest approach standardizes the data for increased accuracy. Some of the supervised learning methods employed are Naive Bayes (NB), Logistic Regression (LR), Random Forest (RF), Decision Tree Classifier (DT), Support Vector Machine (SVM), as well as K-Nearest Neighbor (KNN).

Hammad et al.'s Deep Neural Network (DNN) technique [10] offers a solution to the categorization problems. The method incorporates a learning phase in which trustworthy feature extraction improves classification accuracy. A genetic algorithm (GA) approach is then used to association the best feature extraction as well as classification combinations. Utilizing the MIT-BIH Arrhythmia, five different types of arrhythmias were identified using the Memory for the Advancement of Medical Instrumentation (AAMI) criteria for validation.

Rajdhan et al. [11] worked with machine learning which is used in many different global sectors. There are no exceptions in the healthcare sector. Machine learning may have a important impact on predicting the likelihood of cardiac issues, locomotor abnormalities, and other illnesses. Such information may provide physicians with crucial insights if predicted well in advance, enabling them to customize their diagnosis along with the treatment approach for each patient. We use machine learning techniques to predict likely human cardiac disorders.

In this study, the effectiveness of several classifiers, including DT, NB, LR, SVM, and RF, is compared. We have used multiple signal processing approaches as well as a deep learning method in this work in order to effectively and accurately denoise, segment, compress as well as classify phonocardiography (PCG) data, as described by Chowdhury et al. [12]. The PCG signal is first compressed as well as denoised by means of a multi-resolution examination rooted on the discrete wavelet transform (DWT). The systole interval, the first heart sound (S1), the diastole interval, along with the second heart sound (S2), are then separated into four major parts using a segmentation approach that is created on the Shannon energy envelope as well as zerocrossing.

Kusunose et al. [13] This study looked at whether a Deep CNN (DCNN) could do a better job than cardiologists, sonographers, and resident readers at finding groups of myocardial infarction areas and regional wall motion abnormalities (RWMAs) from traditional 2-dimensional echocardiographic pictures. To reduce inaccurate RWMA readings, an effective intervention must be put in place. In a clinical setting, a DCNN trained with echocardiographic images was expected to provide superior RWMA recognition.

For Wasimuddin et al. [14] Finding and preventing potentially deadly cardiac crises has been the main focus of scientific research. Classical signal processing approaches, machine learning, as well as its subcategories, including deep learning, are widespread ways to analyze and classify the ECG data. Applications for the initial detection as well as treatment of cardiac disorders and arrhythmias are often developed using these techniques. This paper offers a comprehensive assessment of the literature on ECG signal analysis. The procedure of this stage-rooted process model, a summary of earlier studies on the subject comes after the presentation of a stage-based model for ECG signal processing.

Sahoo et al. [15] presented a thorough analysis of the most recent techniques for ECG-based cardiac arrhythmia identification. It uses feature extraction, signal decomposition as well as machine learning approaches for autonomous detection as well as decision-making. The papers include preprocessing, feature extraction, QRS complex detection as well as ECG beat categorization. According to past studies, the automated method of computer-aided decision-making is essential for the real-time detection of cardiac arrhythmias.

In this work, Singh et al. [16] tried to do away with the segmentation steps. This is mostly caused by the rise in complexity in the segmentation process and the system's increasing computational load, which also adds expenses. The real-world heart sound database that was give in to for the PhysioNet/CinC 2016 Test will be categorized as a result of this research. The PCG signal first five seconds are usually examined before the preprocessing procedures since the signal's length might be anywhere between 5 and 120 seconds. The spike elimination approach is then used to reduce the bounties of the unwanted PCG signals. Though many methods have been available they lacked in some ways mostly with better prediction rate or accuracy of the model. Hence there is a need to develop a new model to detect the cardiac disease accurately. Also, many methods did not concentrate to estimate the error rate. Moreover, they also had some issues like exploding gradient etc. So, a new model termed as custom CNN (C-CNN) model is designed with the following contributions:

- The research concentrated on exploding gradient issue by using a softsign activation function other than the normally used relu activation function.
- It then measured a drop rate factor which is responsible to reduce the error rate.
- Additionally, this dropout rate prevents overfitting of the model.
- The performance measures like precision, accuracy, recall as well as f1-score are considered to calculate the proposed C-CNN model performance.

3. Proposed Methodology

The proposed C-CNN model is meant to detect the presence and absence of cardiac disease. The proposed C-CNN model with convolutional layer which is utilised to cutting deep features, which are then passed on to the dense layer. Additionally, a dropout layer, as well as a max-pooling layer are also used. Then, the proposed C-CNN model's dense layer divides the images into two categories such as presence and nonappearance of cardiac heart disease. Figure 1 shows the proposed architecture for a Cardiac Disease Detection System utilizing C-CNN. There are two phases to the proposed model. Feature extraction and a C-CNN classifier are the first two steps.

3.1. Convolutional Layer

In order to extract spectral information, a 1D-CNN model was used. The original input size of the data is first loaded into the 1D-CNN model [17]. Feature extraction is performed on the convolutional layer (Conv). This layer is situated underneath the consecutive layer, in order to get dimensionality-reduced feature data. Utilising 1D-CNN, convergence is carried out throughout the immediate region of input data to generate the corresponding feature. Every kernel on the feature map has unique attributes in every location. 1D-CNNs, which join with fewer limits, employ weight sharing. This guarantees that 1D-CNN will join earlier and faster. All input layer as well as output layer stride will share all weights since the kernel size is set at 3. the kernel window's input values have weights assigned to them. By adding the values, the feature map value is produced. The convolution layer output is utilized as equally the input as well as the output of the next layer. Two convolutional layers stay tracked by one additional in this research [18].

3.2. Pooling Layer

The pooling layer follows the convolutional layer as well as has the capacity to recover lower-resolution feature data and further decrease the dimensionality of the feature vector. Pooling layers are crucial for CNNs. In order to speed up the subsequent phase, pooling decreases the number of parameters while retaining the crucial qualities. As a consequence, each feature map is now examined using the max technique. The max-pooling method is used to choose the extreme limits in the default window. Pooling approaches are also anticipated to tackle the overfitting issue. As input to the layer is flattened, the output values and the highest and lowest values for the subsequent network layer will both be scaled down.

3.3. Dense Layer

To get the overall feature of the information, the output information from the flatten layer are provides into the dense layer or fully connected layer. The ReLU (Rectified Linear Units) function is employed as the beginning function in this research, which may help the network learn challenging information, improve its nonlinear modeling capabilities, as well as provide more precise predictions. The max function is applied to all of the values in the input information, along with each negative value are changed to zero by the ReLU layer. The ReLU beginning function is shown in the equation below.

$$\mathrm{relu}(x) = \max(x, 0) \tag{1}$$

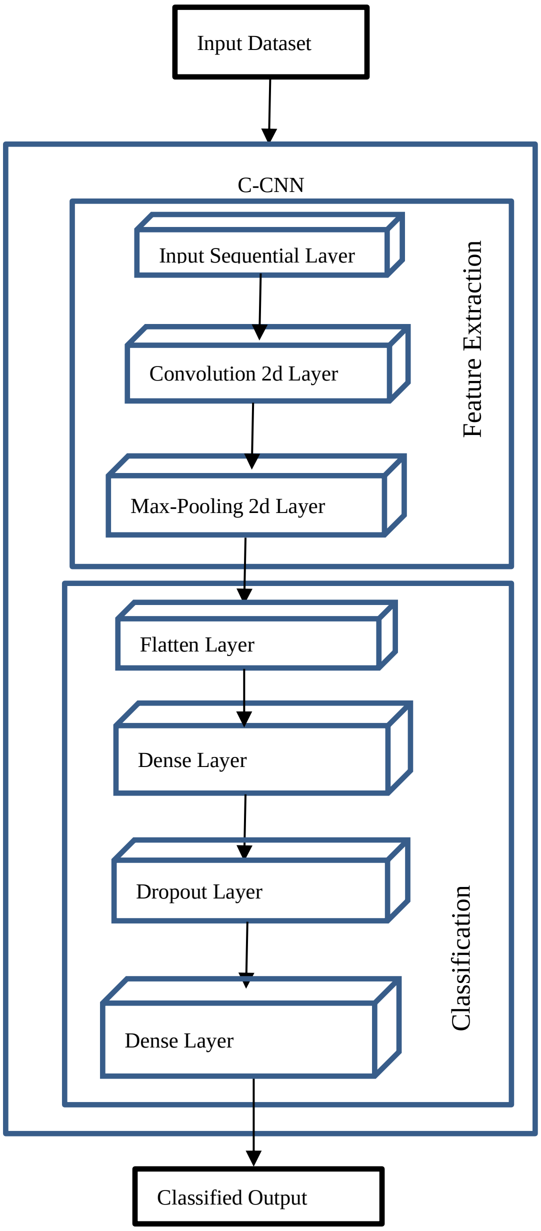


Fig .1. Flow diagram of the proposed work

When dealing with the issue of exploding gradient while training the model, initially the ReLU is used. Furthermore, the exploding gradient is the polar opposite of the vanishing gradient, and it is caused by huge weights. Although, to avoid the problem of a vanishing gradient, a parameterized

ReLU activation function can be useful in avoiding "dead" neurons caused by a standard ReLU setting negative inputs to 0. Because the ReLU activation function is computationally efficient, the network can join quickly. ReLU has a copied function as well as allows for back propagation, despite the detail that it looks to be a linear function. However, as inputs are 0 or negative, the incline function becomes zero, and the network is impotent to do backpropagation or absorb. As a result, backpropagation can be used to determine the best acceptable value of a. The mathematical expression for parameterized ReLU (PReLU) is as in (2):

$$\text{Parmtized\_relu}(x) = \max(x, 0.01x) \tag{2}$$

However, PRELU's performance may vary depending on different problem. Hence in this work, a softsign beginning function is utilized. The softsign beginning function's mathematical expression is expressed in (3)

$$\text{softsign}(x) = \frac{x}{|x|+1} \tag{3}$$

The Softsign function output is centred on 0 as well as compresses the input into the interval between (-1,1). Then the dense layers were utilised to generate class scores from the beginnings utilized in classification. A crucial component is the fully connected (FC) layer of CNN. The CNN approach separates the input into a features vector and then examines each feature separately. The initial phases in this process are convolution and pooling. A final judgment that is entirely tied to the process is the outcome. The output of the network's former levels is reshaped (flattened) to produce a only vector. All one reflects the propensity of a certain attribute to be a class label. To choose the appropriate label, weights and the feature map are utilized as input. Adam is a device that helps with optimization. Since Adam converges significantly more rapidly than other adaptive techniques, it has recently been referenced in the majority of research literature. The cardiac heart disease is then identified using the output from the prediction process. The dense layer provides the last probability for each label.

4. Results and Discussion

4.1. Dataset

The ML Repository at UCI was used to get the dataset [19]. The variables in this dataset may be used to recognize people who are at a high danger of developed heart disease. Age, trestbps, sex, cp, chol, fbs, restecg, exang, ca, thalach, thal, oldpeak, slope, along with target are the characteristics in the dataset. Fig 2 displays the heatmap of the figure.

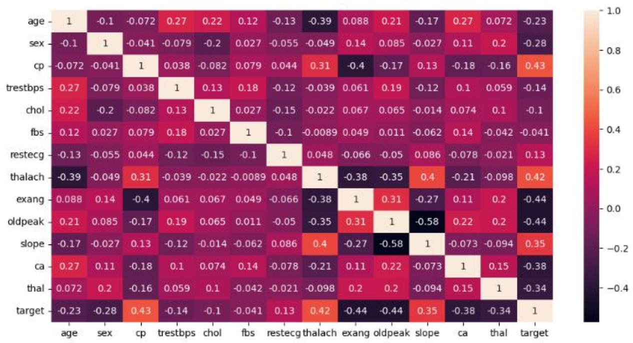


Fig. 2. Dataset Heatmap

The parameters employed in the proposed C-CNN model are described in Table 1. Convolutional layer is the first layer with the custom softsign beginning function. The pooling layer, is the consequent second layer with pool size as 2. The third layer is the one that is flattened. The fourth layer, the dense layer, also has a custom softsign activation function and 128 units. The dropout layer is the next fifth layer with 0.5 as dropout rate. The final is a dense layer with one unit meanwhile the proposed work is a two organisation, along with the beginning function is sigmoid meanwhile it is careful best for two organisations. Adam's optimizer, binary cross entropy, and 50 epochs make up the additional training limits.

Table 1. Proposed C-CNN model parameters

Layer	Type	Parameter
Conv1D	Convolutional layer	Filters = 64, kernel size =3, activation = custom softsign, input shape = (13,1)
Maxpooling1D	Pooling layer	Pool size =2
Flatten	Flatten layer	-
Dense	Dense layer	Unit =128, activation = custom softsign
Dropout	Dropout layer	Drop rate = 0.5
Dense	Dense layer	Unit =1, activation = sigmoid

A critical step in determining how well a model might function with hypothetical data is to assess its performance. This research has compared the proposed C-CNN model with the existing CNN model using eight different metrics. With the use of these metrics, it is feasible to evaluate the data's relevance for each classification label and to contrast several models with one another. F1 score, accuracy, recall, precision, confusion matrix, macro average, support, and weighted average are the metrics. The percentage of correctly recognized observations among all observations is how accuracy is calculated. It serves as a first indication of model success by providing data on the percentage of inputs that are correctly recognized. Accuracy is expressed mathematically in (4).

$$\text{accuracy} = \frac{\text{Proporly identified observations}}{\text{All Observations}} \quad (4)$$

The confusion matrix tabulates the forecasts for every model. Each row in this matrix represents a prediction made for each class, while the columns of this matrix indicate actual class classifications. Meanwhile equally the rows as well as the columns identify classes, the leading diagonal demonstrates how well the model predicted the data. Terms like false negative (FN), false positive (FP), true negative (TN), true positive (TP) are utilized for full evaluation.

The precision measure is employed to evaluate the model's accuracy estimates for a certain class. It reveals that, out of all the forecasts, the model's estimate that the output would fit to a specific class was correct. This number tells us how accurate the model is for all class. It may be designed for all class by dividing the proportion of TP by the quantity of TP along with FP. In (5), precision is given.

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

Recall is defined as the proportion of correctly identified samples to every sample in that class as determined by the model. It is also termed as "sensitivity," as it indicates how the model sensitives to the presence of a certain class. In (6), recall is equivalent.

$$\text{recall} = \frac{\text{TP}}{\text{FN+TP}} \quad (6)$$

The F1 Score metric, a harmonic ratio, assists in achieving a balance between recall and accuracy. (7) equates the F1 score.

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

Support offers data on the overall incidence of models belonging to a certain class. This makes the number of samples used in the research visible and enables class-wise delivery analysis of the dataset. Both a weighted average and a macro summary of all these indicators are possible. The entire of the acquired values of a metric, such as recall, accuracy, f1 score, etc., are designed when all of the classes are combined together to create a macro-average. The sum is then divided by the overall number of classes. This is represented numerically in (8).

$$\text{Macro avg} = \frac{\text{class 1 score +class 2 score}}{2} \quad (8)$$

A weighted average is a form of averaging that takes into explanation the unable sample delivery of classes in the data collection. This may be expressed mathematically as (9), where the creation of the metric score got for all class is added to the count of samples that are part of that class (the support value) and then divided by the total count of samples.

$$\text{Weighted avg} = \frac{\sum(\text{ith class score} * \text{ith class support})}{\text{total count of dataset samples}} \quad (9)$$

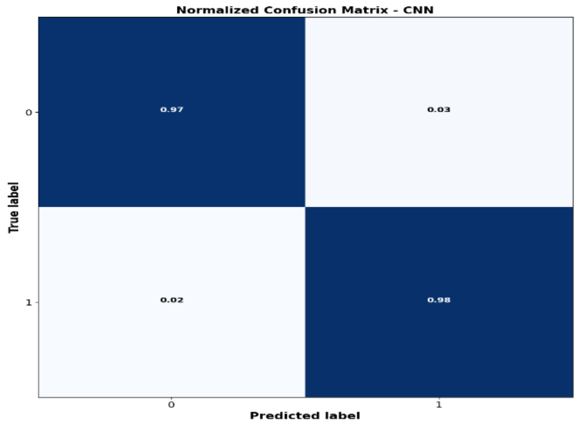
4.2. Discussion

This section gives the assessment of the proposed C-CNN model for cardiac heart disease organisation is complete with existing CNN. The assessment outcomes are tabulated in table 2.

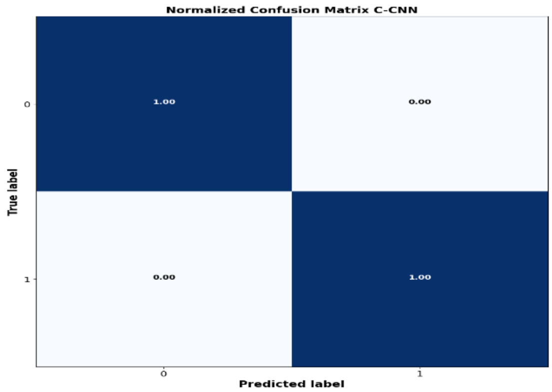
Table 2. Comparison Table

Method	Classes	precision	recall	F1-score	Support
CNN	0	0.98	0.97	0.98	106
	1	0.97	0.98	0.97	99
	Accuracy			0.98	205
	Macro avg	0.98	0.98	0.98	205
	Weighted avg	0.98	0.98	0.98	205
Proposed C-CNN	0	1.00	1.00	1.00	106
	1	1.00	1.00	1.00	99
	Accuracy			1.00	205
	Macro avg	1.00	1.00	1.00	205
	Weighted avg	1.00	1.00	1.00	205

The comparison of performance metrics for various methodologies is shown in Table 2. The proposed model appears to provide improved outcomes than the existing CNN model when all the parameters are compared. The precision, F1-score, macro average, accuracy and weighted average of the proposed C-CNN model is 2.04% better than the existing CNN. The recall of the proposed C-CNN model is 3.09% better than the existing CNN. Additionally, Fig 3 shows the confusion matrix graph for these models. Fig 4 illustrates the existing CNN accuracy as well as loss graph. Fig 5 illustrates the proposed C-CNN model accuracy as well as loss graph. Fig 6 illustrates the existing CNN along with proposed C-CNN model accuracy as well as loss graph.



(a)



(b)

Fig.3. Confusion Matrix (a) Existing CNN (b) Proposed C-CNN model

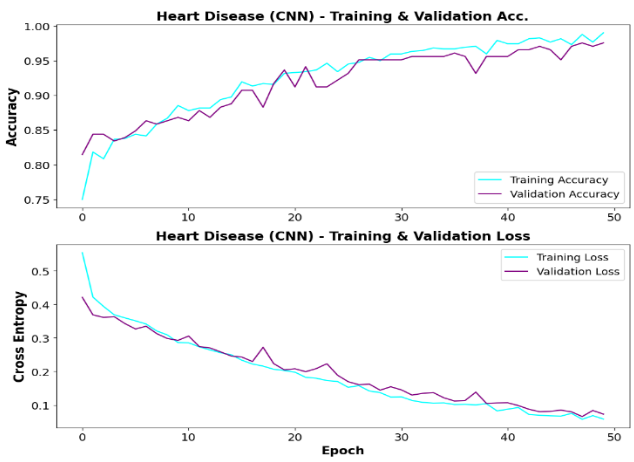


Fig.4. CNN accuracy and Loss Graph

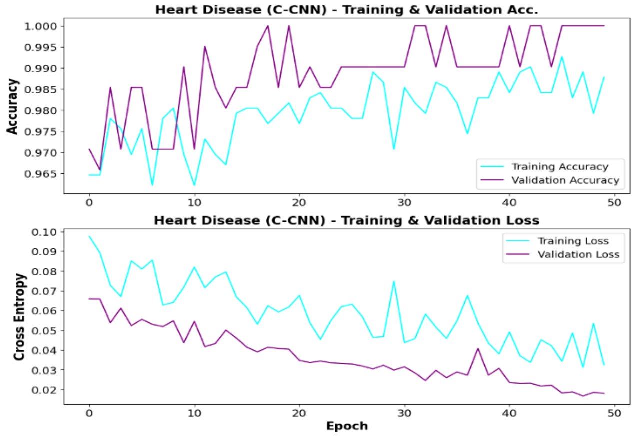


Fig.5. Proposed C-CNN model accuracy and Loss Graph

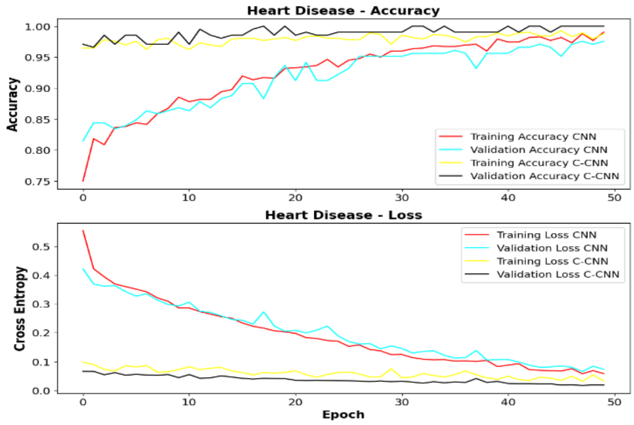


Fig.6. Existing CNN and proposed C-CNN model accuracy and Loss Graph

Figures 4, 5, and 6 show the training accuracy and training loss improvement graphs. The proposed C-CNN model performs better in terms of accuracy than the existing CNN model and performs worse in terms of loss. As a result, it has been shown that the proposed C-CNN model diagnoses cardiac heart disease more accurately than other existing models.

There are limits, even if the proposed study has improved coronary heart disease prediction to this point. Additionally, deep learning algorithms are employed in this study in addition to machine learning algorithms to accurately diagnose cardiac heart problems. Therefore, by using a combination of these two methods, this work may be expanded.

5. Conclusion and Future Work

This research uses the C-CNN model to identify cardiac heart disease. The proposed model's efficacy is investigated with the help of the current CNN in order to conduct a comparison analysis and get really effective results. This study came to the conclusion that the proposed C-CNN model outperformed statistical techniques significantly. This study's conclusions, showing this model is the best way to predict and classify cardiac heart disease, are supported by the findings of this paper. Several performance indicators have been compared using the UCI data set. The algorithm will be further improved by more research.

Conflict of Interest

None

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