# Novel Deep Learning Architecture for Heart Disease Prediction using Convolutional Neural Network

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Abstract — Healthcare is one of the most important aspects of human life. Heart disease is known to be one of the deadliest diseases which is hampering the lives of many people around the world. Heart disease must be detected early so the loss of lives can be prevented. The availability of large-scale data for medical diagnosis has helped developed complex machine learning and deep learning-based models for automated early diagnosis of heart diseases. The classical approaches have been limited in terms of not generalizing well to new data which have not been seen in the training set. This is indicated by a large gap in training and test accuracies. This paper proposes a novel deep learning architecture using a 1D convolutional neural network for classification between healthy and non-healthy persons to overcome the limitations of classical approaches. Various clinical parameters are used for assessing the risk profile in the patients which helps in early diagnosis. Various techniques are used to avoid overfitting in the proposed network. The proposed network achieves over 97% training accuracy and 96% test accuracy on the dataset. The accuracy of the model is compared in detail with other classification algorithms using various performance parameters which proves the effectiveness of the proposed architecture.

Keywords— Heart Disease Prediction, Healthcare, Deep Learning, 1D Convolutional Neural Network, Embedding Layer, Overfitting

## I. Introduction

There has been considerable research in the field of healthcare in the last few years particularly after the Covid pandemic. It has been observed that heart diseases are one of the deadliest diseases which cause maximum deaths of human lives in the world according to the world health organization [1]. It is also observed that more than 24% of the deaths in India are due to various forms of heart disease [2]. So there is a need to develop an early diagnosis system that prevents the deaths which are occurring due to heart diseases.

Heart diseases or also known as cardiac diseases are generally caused by the narrowing of coronary arteries which supply blood to the heart. There are methods like Angiography which is used for detecting heart diseases but it is very costly and is prone to certain reactions in a patient's body. This prevents widespread use of these techniques in countries with large poor populations.

There is a need of developing healthcare products that provide quality results at an affordable rate. The healthcare organizations are also looking for clinical tests which can be performed without invasion at a cheap rate. The development of a computer-based decision support system for the diagnosis of various diseases can help organizations cater to the need of millions of people around the world.

The rapid growth of machine learning and deep learning algorithms has helped research in various industries including medical. The availability of large-scale medical diagnosis data has helped in training these algorithms. The clinical support system can be developed using these algorithms which helps in reducing cost and increasing accuracy [3].

Various clinical features can be utilized by machine learning algorithms for categorizing the risk profile of the patients. There are certain features like age, sex, heredity which are not in control while features like blood pressure, smoking, drinking habits are in control of the patient [2]. The proposed algorithm uses a combination of these features for categorizing healthy and non-healthy patients.

The remainder of the paper is organized as follows: The existing methods of heart disease classification using machine learning solutions are discussed in Section-II. The explanation of the proposed architecture is explained in Section-III. The implementation details and results are discussed in Section-IV.

# II. LITERATURE SURVEY

There has been a lot of research in developing a heart disease diagnosis system for early detection using various clinical parameters. Various Classification algorithms like Logistic Regression, Support Vector Machine, Decision Tree,

Random Forest, Artificial Neural Network, etc are being used for classifying patients. This section summarizes those implementations.

S. Radhimeenakshi [4] proposed a Decision Tree and Support Vector Machine for heart disease classification. He concluded that the decision tree classifier performs better than SVM in terms of accuracy measured using a confusion matrix.

R.W.Jones et al [5] proposed a heart disease prediction technique using an artificial neural network. They used a self-applied questionnaire for training the neural network. The neural network contained three hidden layers and was trained using a backpropagation algorithm. The architecture was validated using the Dundee rank factor score and achieved a 98% relative operating characteristic value on the dataset.

Ankita Dewan et al. [6] compared the performance of genetic algorithms and backpropagation for training the neural network architecture. They concluded backpropagation algorithms perform better with a very minimum error on the dataset. SY Huang et al. [7] proposed a learning vector quantization algorithm for training the artificial neural network. They used 13 clinical features for training the network and achieved almost 80% accuracy on the dataset.

Jayshril S. Sonawane et al. [8] proposed a new artificial neural architecture that can be trained using a vector quantization algorithm with random order incremental training. They also used 13 clinical features for training and achieved 85.55% accuracy on the dataset. Majid Ghonji Feshki et al. [9] used four different classification algorithms which include C4.5, Multilayer Perceptron, Sequential Minimal Optimization, and feed-forward backpropagation. They concluded that the PSO algorithm with neural networks achieved the best accuracy of around 91.94% on the dataset.

R. R. Manza et al. [10] proposed an Artificial Neural Network with many numbers of Radial Basis Function neurons in the hidden layer. They obtained around 97% accuracy on this architecture. Saba Bashir et al. [2, 10] proposed a hybrid model for heart disease prediction which uses a combination of decision tree, SVM, and Naïve Bayes algorithms. They achieved 74% sensitivity, 82% accuracy, and 93% specificity.

P. Ramprakash et al. [1] proposed a deep neural network and  $\chi^2$  statistical model for feature selection. They used various techniques to avoid overfitting and underfitting. They achieved 94% accuracy, 93% sensitivity, and 93% specificity. Turay Karayilan et al. [2] studied the performance of artificial neural networks with the various number of hidden layers. They achieved around 95.55% accuracy using five hidden layers.

It can be observed that most of the proposed systems use Artificial Neural Networks with some modifications. It is observed that these architectures are prone to overfitting so perform poorly on new data. So this paper proposes a new architecture using a one-dimensional convolutional neural network with dropout to avoid overfitting. It uses the Cleveland database [12] which has 13 features for classifying between healthy and non-healthy patients. The other classification algorithms are also implemented for verifying

the performance of the proposed architecture using well-known performance measuring parameters.

A detailed explanation of the proposed architecture with the algorithms and techniques used in the next section.

## III. PROPOSED ARCHITECTURE

This section describes the proposed architecture and all its constituent layers in detail along with the techniques used to optimize the architecture. It also gives some theoretical background about the 1-D convolutional neural network (CNN) which is central to the proposed architecture.

Conventional 2D CNN has become very popular in pattern recognition problems like Image classification and object detection [13]. CNNs are similar to ANN in which they consist of self-optimizing neurons which are trained to perform a certain task. This has led to the development of 1-D CNN which can operate on one-dimensional dataset or Time series data [13]. The proposed architecture using this concept of 1D CNN is shown in figure 1 below.

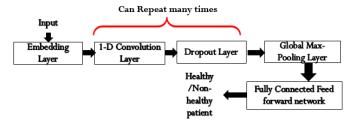


Figure 1: Proposed 1-D CNN Architecture

The input to the architecture will be the 13 features that are important in the classification of heart disease. These features are converted to a new representation called word embedding by the layer called as Embedding Layer. It is similar to the Bag of Words concept used for Text data. It helps in a better representation of the dataset according to unique values present in each of the features. The output of the Embedding layer is given to the 1D CNN layer for feature extraction.

1D CNN is very similar to conventional 2D CNN but the convolution operation is only applied to the one dimension which results in shallow architecture which can be easily trained on normal CPU or even embedded development boards [13]. The convolution operation helps in finding useful hierarchical features from the dataset which are useful in classification. The dimensions of the output features after 1D CNN can be calculated using the equation given below:

$$x = \frac{w+2p-f}{s} + 1 \tag{1}$$

Where x is the dimension of output features and w is the size of input features. f indicates the size of the filter used for convolutions. 'p' indicates padding which are values added on the boundary before applying convolution. 's' indicates stride which is the value traveled after applying convolution operation.

The 1D convolution operation is a linear operation that is not useful in classifying nonlinear data. Most of the real-world dataset is nonlinear which requires some nonlinear operation after convolution. This nonlinear function is called an activation function. Sigmoid, hyperbolic tangent, and rectified linear unit (RelU) are some of the widely used activation functions. The proposed architecture uses the RelU activation function which is easy to compute and allows faster computation. It also does not suffer from vanishing or exploding gradient problems.

There can be multiple convolution layers in the architecture followed by an activation function. The proposed architecture uses two 1-D convolution layers with 128 filters and filter sizes of 3. The output of the final convolution layer is passed through the global max-pooling layer which pools the maximum value from all the channels and reduces the dimension of output. The output of pooling is passed through the fully connected layer with 256 neurons which extracts the useful features for classification. This layer is similar to the hidden layer is ANN. The final layer contains a single neuron which gives the classification probability. The final layer uses the sigmoid activation function as it directly gives the probability for binary classification.

The layer-wise details along with output feature dimensions and the number of trainable parameters are shown in Table 1.

**Table 1: Layerwise CNN Architecture** 

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Layer (type)	Output Shape	No. of Parameters	
Embedding_1 (Embedding)	(None, 13, 300)	45600	
dropout_1 (Dropout)	(None, 13, 300)	0	
Conv1d_1 (Conv1D)	(None, 13, 64)	57664	
dropout_2 (Dropout)	(None, 13, 64)	0	
Conv1d_2 (Conv1D)	(None, 13, 64)	12352	
Global_max_pooling1d_1 (GlobalMaxPooling1)	(None, 64)	0	
dense_1 (Dense)	(None, 256)	16640	
dense_2 (Dense)	(None, 1)	257	
Total parameters: 132,513			
Trainable parameters: 132,513			
Non-trainable parameters: 0			

The proposed 1D CNN architecture contains around 0.13 million trainable parameters which will get adapted during training of the network. It was observed that general CNN architecture overfitted the training data meaning that training accuracy was very high and validation accuracy was low. The dropout technique was introduced to remove overfitting. It removes random neurons with a certain probability during training which allows the different

networks to be trained at every iteration. This will help in the network not being too dependent on any single neurons of the network. The dropout layer has been introduced after each trainable layer in the proposed architecture. The addition of the dropout layer helped the training and test accuracy to be very similar which points to the network adapting well to data that it has not seen.

The next section describes the implementation details and results obtained after training the proposed architecture.

#### IV. IMPLEMENTATION AND RESULTS

The proposed architecture for heart disease prediction has been implemented using scikit-learn and Keras library which allows the implementation of various machine learning and deep learning algorithm. The system used for development contains an intel i5 CPU and 8GB RAM. It also has GeForce 940 GPU which helps in training the architecture faster.

The paper uses the Cleveland database [12] which has 303 samples of patients with 14 different features. The dataset is divided into two parts. 80% is used for training and the remaining 20% is used for validation. The features used for classification in the dataset are explained in Table 2.

**Table 2: Dataset details** 

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Sr	Feature	Value Range		
No.				
1	Age of Patient	29-77		
2	Gender	1 = Male		
		0 = Female		
3	Category of Chest Pain	0 = Atypical		
		Angina		
		1 = typical		
		Angina		
		2 = Asymptotic		
		3 = Non Angina		
4	Blood Pressure	94-200		
5	Serum Cholesterol Level	126-564		
6	Fasting Blood Suger	0 if < 120		
		1 if >= 120		
7	Resting ECG result	0 = Normal		
		1 = ST-T wave		
		abnormalities		
		2 = left		
		ventricular		
		Hypertrophy		
8	Heart rate	71-202		
9	Exercise-induced Angina	$0 = N_0$		
		1 = Yes		
10	ST depression due to	0 - 6.2		
	exercise-related to rest			
11	The slope of the peak	0= un sloping		
	exercise ST segment	1=flat		
		2=down sloping		
12	Count of major	0-3		
	vessels colored by			

	Fluoroscopy	
13	Thallium Scan	3=normal 6=fixed 7=reversible effect
14	Heart Disease	0 = No 1 = Yes

Some of the attributes have missing values for some of the examples. Those values have been replaced with the mean value of that attribute for training our architecture. Most of the traditional classification architectures require all the attributes in the same range. This dataset has attributes in different ranges so a standardization technique is applied which converts all the attributes into the same range. It subtracts all the attribute values with the mean value of the attribute and divides by the standard deviation of the attribute. The final attribute is the true label for the patient whether he/she has heart disease or not. The dataset is a little unbalanced in the sense that there are more negative examples compared to positive as shown in figure 2 below.

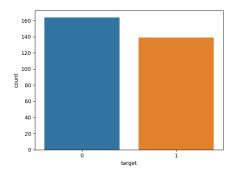


Figure 2: Distribution of labels in the dataset

As can be seen in figure 2, there are 163 negative examples and 140 positive examples in the dataset. The first 13 attributes are used as input features for classification. The proposed architecture is trained for 150 epochs with a batch size of 32. The binary cross-entropy function is used as a loss function to calculate the loss between the true value and the predicted value. This function has to be minimized using some optimization algorithm to achieve convergence. The Adam optimization algorithm is used for training as it provides faster convergence and does not zigzag around the local minima [14].

ADAM uses exponentially weighted gradients as well as exponentially weighted square gradients for updating the weights at each iteration.

Exponentially decaying averages of past gradients is calculated by:

$$m_{t} = \beta_{1} m_{t-1} + (1 - \beta_{1}) g_{t}$$
 (2)

Where  $m_t$  is the momentum term at timestamp 't',  $\beta_l$  is constant which is taken as 0.9 and  $g_t$  is the gradient at timestamp 't'. Exponentially decaying averages of past squared gradients is calculated by:

$$v_{t} = \beta_{2} v_{t-1} + (1 - \beta_{2}) g_{t}^{2}$$
(3)

Where  $v_t$  is the velocity term at timestamp 't',  $\beta_2$  is constant which is taken as 0.99 and  $g_t$  is the gradient at timestamp 't'.

Bias correction  $\hat{m_t} = \frac{m_t}{1 - \beta_1^t}$  and  $\hat{v_t} = \frac{v_t}{1 - \beta_2^t}$  and then, update parameters using Adam's update rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\nu_t + \epsilon}} \hat{m}_t \tag{4}$$

Where  $\varepsilon$  is constant with a very small value which avoids division by zero and  $\theta_t$  is a parameter value at timestamp 't'.

The training and test accuracy after each epoch is shown in figure 3 below:

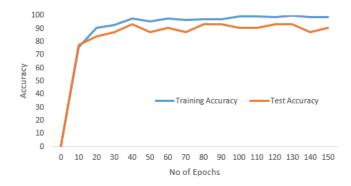


Figure 3: Accuracy after each epoch using Adam
Optimizer without Dropout

The proposed architecture achieves 98.9% accuracy on the training set and 90.32% on the test set. There is a large gap between training and test accuracies which indicates overfitting in the architecture. Dropout layers are added after every trainable layer in the architecture with a probability of neurons being removed is 0.3. The train and test accuracy at every epoch for the modified architecture is shown in figure 4.

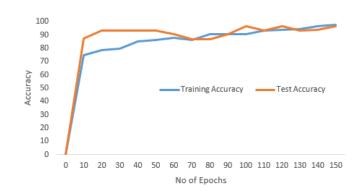


Figure 4: Accuracy after each epoch using Adam Optimizer

The proposed architecture achieves 97.79% accuracy on the training set and 96.77% on the test set. Some other

Table 3: Performance Comparison of Proposed Architecture with other Classifiers

Algorithm	Training Accuracy	Test Accuracy	Precision	Recall	F1 Score	AUC
Logistic Regression	86.36	80.32	85	65	73.5	78.0
Naïve Bayes	86.77	78.68	78.26	69.23	73.46	77.47
SVM	92.56	80.32	85	65.3	73.9	78.4
Decision Tree	100	77.04	73.07	73.07	73.07	76.53
Random Forest	99.17	77.04	77.23	65.38	70.83	75.54
LightGBM	99.58	77.04	83.33	57.69	68.18	74.56
XGBoost	100	78.68	84.21	61.53	71.11	76.48
Artificial Neural Network	88	78.68	78.26	69.23	73.46	77.47
Proposed Architecture (1D CNN)	97.79	96.77	94.73	100	97.29	96.15

The accuracy is measured in terms of the ratio of the total number of correctly classified examples to total examples. It can be from the table that the proposed architecture is the best performing architecture in terms of test accuracy. Some other architectures perform well on the Training set but perform very poorly on the test set. The accuracy can alternatively be represented as a confusion matrix. It has the number of correctly classified examples in the diagonal and wrongly classified examples elsewhere. The confusion matrix for the given architecture is shown below in Table 4.

**Table 4: Confusion Matrix** 

	Predicted Class		
Т		0	1
True Class	0	24	2
	1	0	36

When the dataset is unbalanced then sometimes accuracy does not give a correct idea about the performance measure of the architecture. So, the performance is also measured in terms of other performance measuring parameters like precision, recall, F1 Score, and area under the ROC curve (AUC).

Precision is an indication of how many positive predictions are correct whereas recall identifies how many actual positive examples are correctly identified. There is always a tradeoff between precision and recall so a new performance measuring parameter F1 score is introduced. F1 score is a harmonic mean of precision and recall which gives a balance value between precision and recall.

The last parameter AUC is a measure of the area under the receiver operating characteristic curve. The ROC curve is shown in Figure 5.

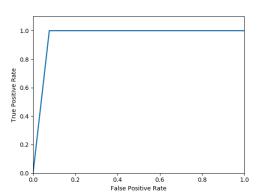


Figure 5: ROC curve

The ROC curve is the plot between false positive rate and true positive rate. The proposed architecture has a ROC curve that is very near to the ideal curve which indicates the good performance of the architecture on the test set.

The proposed architecture performs well in terms of all of these performance parameters. The proposed architecture is also verified on new data which is not available on either train or validation set. It achieves good performance on new data as well. The statistical importance of each feature in classification is also observed.

# V. Conclusion

The goal of this paper is early diagnosis of heart disease using a computer-assisted system. This paper proposes a 1D convolutional neural network architecture for predicting heart disease. It also contains an Embedding layer which converts the feature vector into new vector embedding which helps in classification. The proposed architecture is implemented as a software system on a computer that can help in the early diagnosis of heart disease at a cheap cost and with high accuracy. The architecture uses overfitting avoidance techniques which helps the performance of unseen data. The performance of 1D CNN architecture is best among all other

classification algorithms like Logistic Regression, Naïve Bays, SVM, Decision Tree, Random Forest, LightGBM, XGBoost, and ANN. More and more parameters can be included in the system which can help in classifying heart disease more accurately. It can also be integrated with wearable sensor readings for real-time prediction of heart diseases.

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