

# Optimized Hyperparameter Tuning of the Deep Neural Network Towards Heart Disease Classification on Feature Selected Using Particle Swarm Optimization

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## ABSTRACT

Heart disease is a complex disease in healthcare industry as it leads to large number of death around the world. Early detection and classification of the disease using computer vision technique increase the survival rate of the patients. Especially machine learning technique has been employed to electronic health records of the patients. Due to class imbalance, high dimensionality and data sparsity issue of the dataset, machine learning model finds it complex to detect and classify the disease with reduced accuracy. In order to manage those mentioned challenges, a new paradigm termed as deep learning architecture can be employed. In this article, a new optimized hyperparameter tuning of deep neural network architecture has modeled and implemented along the particle swarm optimization considered as feature selection technique is incorporated along the proposed architecture to generate the optimal feature towards classification and identifying the severity of the disease on the patients. Further proposed method is constructed as oversampling technique to eliminate the overfitting issues and class imbalance issues on feature distributions. Hyperparameter tuning of deep neural network is to compute best hyperparameter for classification of the disease. Activation function of the model uses parameterized Rectified Linear Unit for forward propagation of the feature for classification with weight updating. Classification layer is regularized through batch normalization on setting the epoch value for training the dataset. Cross validation of the model on validation data is processed in loss layer using cross entropy function to achieve better accuracy in process of detection and classification. Experimental analysis of the proposed model is evaluated using two benchmark dataset which represented as Cleveland dataset and ORBDA -electronic health record. The results depicts that proposed model achieves high accuracy and less execution time on comparing against the state of art approaches. Model achieves 99.14 percent accuracy on the Cleveland dataset and 98.45 percent on the ORBDA dataset respectively.

**Keywords:** Cardio Vascular Disease Classification, Convolution Neural Network, Particle Swarm Optimization, Principle Component Analysis, K-Nearest Neighbour, Z- Score Normalization, Missing Value Prediction, Singular value Decomposition

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### Introduction

Heart disease is investigated as growing cause of the mortality around the world and especially it become complicated to healthcare industry while covid -19 pandemic. Heart disease is largely distinguished with respects to variation of pressure in the blood flows into vessels and artery. Especially rheumatic heart disease is represented highly contributing factor for heart disease. However other types of heart disease outcomes were due to many disease comorbidity such as covid -19 inspection, Stroke, Hypertensive Heart Disease(HHD), Congenital Heart Disease(CHD) cardiomyopathy(dilated/hypertrphic/ restrictive), Valvular Heart Disease(VHD), Carditis, Aortic Aneurysms, Peripheral Artery Disease(PAD), thromboembolic disease, arterial thrombosis and venous thrombosis[1].

Furthermore, multiple complication of the heart diseases causes due to changes of numerous health factors of patients along other disease such as diabetics, cancer, periodontal diseases. Hence predicting the disease comorbidity with cardiovascular disease is high challenging to diagnosis. Hence it leads to requirement of many research model in the medical community for intelligent heart disease prediction and classification model on changing health condition of the patient. Recently Electronic health Records were considered as dataset for heart disease research model as it contains medical records representing wide information of the patients. Further it provides various insight to the research model towards diagnosis of the patient health using learning model. Electronic Health Records is becoming vital data collection to early diagnosis of disease trough data analytics.

Traditionally Heart disease diagnosis is employed as manual and automated diagnosis approaches. However Manual approaches lead to inappropriate detection and irrelevant disease classification[11]. In order to obtain accurate and reliable heart disease classification [2], Big Data Analytics using artificial intelligence approaches especially machine learning and deep learning techniques has to be presented to obtain the accurate results [3]. Despite of large benefits of machine learning and artificial intelligence techniques , it leads to more challenges on processing the EHR dataset as it contains over fitting, curse of dimensionality and data sparsity issues which makes inappropriate for disease prediction and disease classification. To alleviate the above represented complications, an optimized hyperparameter tuning of deep neural network is designed as a disease classifier to attain accurate disease classification with following design specification as current methodologies[12].

In this article, Optimized hyperparameter tuning of the deep neural network to feature selected using particle swarm optimization has been implemented to classify the optimal features for effective cardiovascular disease classification. Current approach is to classify heart disease data into various types with enlarged feature set. In this current design specification, approach for missing value prediction, data normalization and dimensionality reduction has been included as pre-processing step to EHR dataset. Pre-processed EHR dataset is employed to principle component analysis approach representing for feature extraction process[13]. Extracted disease feature is defined to particle swarm optimization approach to identify the suitable feature set to disease classification. Finally classifier is tuned with various constraints and strategies as deep learning process on the various data processing layer of the Deep Neural Network(DNN) towards disease classification.

The remaining part of the research article is partitioned as follows; Section 2 mentions the machine learning and deep learning model significant to the current dataset and architecture for classification of heart disease. Section 3 mentions the design specification of the current architecture to classify the heart disease on various setting the hyperparameter and activation function on the layer of the current model to classify the heart disease. Experimental outcomes of the current approaches is validated and assessed against the state of art approaches using multiple performance measures is mentioned in the section 4 along the benchmark dataset description. Finally section 5 summarizes the major findings of the research article.

## **Related work**

In this section, strong analysis of significant technique suitable for the heart disease classification using machine learning classifier and deep learning classifiers is investigated with its major advantageous and drawbacks.

### **1.1.Convolution Neural Network**

In this literature, Convolution Neural Network(CNN) is employed on the dataset of the heart diseases is analyzed as it belongs to deep learning paradigm. Convolution neural process each disease feature on generating the feature map in the convolution layer as low level feature map and max pooling layer as high level feature map. Generated feature map is employed for fully connected layer towards prediction and classification with support of softmax layer to carry out classification task and activation layer for generate the classes to the feature map[14]. Model produces the accuracy of 98.4%. However it is unsuitable for voluminous data since it can be computationally costlier [4].

## **Proposed model**

In this part, a new design architecture entitled as Optimized hyperparameter tuning of the deep neural network which is to diagnosis the heart disease and to classify the disease employing Metaheuristic technique treated as particle swarm optimization. The details of each component of the current framework to classify the heart disease is as mentioned

### **3.1. Data Pre-processing**

Increased dimensional medicinal datasets in form of high dimensional data is highly complex towards disease classification. Hence Data Pre-processing is employed initially to produce the suitable data format for data classification using data cleaning, missing value prediction, data Normalization and dimensionality reduction approaches. Resultant data is considered as low dimensional data to attain efficient disease classes

#### **1.1.1. Missing Value Imputation- K-Nearest Neighbour Approach**

High dimensional medicinal data composed of the attributes with a missing value is processed using K-Nearest Neighbour approach to fill a missing value to the missing [6]. It is carried out on computation of the centroids value to the missing attribute. Centroid is computed using mean and standard deviation measures[15]. Computed Centroids use the Euclidean distance function to identify the nearest value. Top Selected Nearest Value to centroids is considered as the missing values of the attribute.

#### **1.1.2. Data Dimensionality Reduction - Singular Value Decomposition**

In this part, Singular Value Decomposition(SVD) Approach is presented to convert into low dimensional data from high dimensional data on minimizing the noisy and outlier attribute of the dataset. It uses linear transformation approach[16] as it is capable of avoiding the over fitting challenges on feature classification. Reduced dataset is represented in the vector space model containing domain adapted parameters [7]. Each dimension of the EHR dataset is processed using vector space model which transform the vector to matrix is mentioned as

Matrix of EHR dataset  $E_m = D \sum_{i=0}^n V \dots\dots Eq.1$

Where V is represented as vector form of the dataset

U is represented as the Domain Parameter

Matrix operation of the data minimizes the dimensions of the dataset on considering only domain adapted attributes.

### **1.1.3. Data Normalization – Z Score Normalization**

Data normalization is to generate the resultant records of the reduced domain adapted attributes under a specific range method. Z-Score normalization method is employed to normalize the domain adapted attributes value in the specific range on computation using mean and standard deviation measures such that it normalize (transform or rescale) each input values of resultant feature vector as subsequent features with unit variance and a zero mean [8]. Each record,  $X_{i,n}$  in the dataset is changes into  $X'_{i,n}$ . It is also represented as zero-mean normalization[17]. The normalized attribute is mentioned as

$$\text{Data Normalization } X'_{i,n} = \frac{X_{i,n} - \mu}{\sigma_i} \dots \text{Eq.2}$$

Where  $\mu$ , treated the mean of the specified patient attribute and  $\sigma_i$  as standard deviation value of  $i_{th}$  patient attribute respectively

### **1.2. Feature Extraction – Principle Component Analysis**

Principle Component Analysis [9] is applied to extract the disease specific attributes as features from the normalized dataset. Normalized dataset is represented in the matrix form. Principle component of the resultant dimensions of the matrix is utilized. In that dimensions, the dimension with highest variability (covariance) of the instances and the dimension with least variability (Correlation) of the instances is gathered. In that covariance and correlation matrix, Eigen vectors is computed with eigen values representing disease specific attribute and its value[18]. Those eigen vector represents attributes and Eigen value represents attribute value.

Eigen vectors of the disease attribute  $\alpha_j = \sum q_j^T x$  where  $j=1,2,\dots,m$  ....Eq.3

Eigen Value of the  $\alpha_j$  contains the principle disease attribute sets is  $\{f_1, f_2, f_3, \dots, F_n\}$

### **1.3. Feature Selection using Particle Swarm Optimization**

Particle Swarm Optimization(PSO) is represented as metaheuristic technique is employed to principle disease attributes to derive the optimal features. PSO approach produces the significant feature of the heart disease. In PSO, particle and velocity parameters and fitness function computation is carried out on determining the attribute weights to disease heuristics[19]. Fitness function of the particle swarm optimization is mentioned as

Fitness function = Maximum ( features on specified disease heuristics)

Optimal feature is Calculated as

$$V = v + w_1 * \text{rand} * (L\text{Best} - p) + w_2 * \text{rand} * (g\text{Best} - p) \dots \text{Eq.4}$$

Where V is the fitness attribute selected for disease classification

P is the particle or suitable disease attribute

W1 and W2 is represented as attribute weight of the specified disease matrix

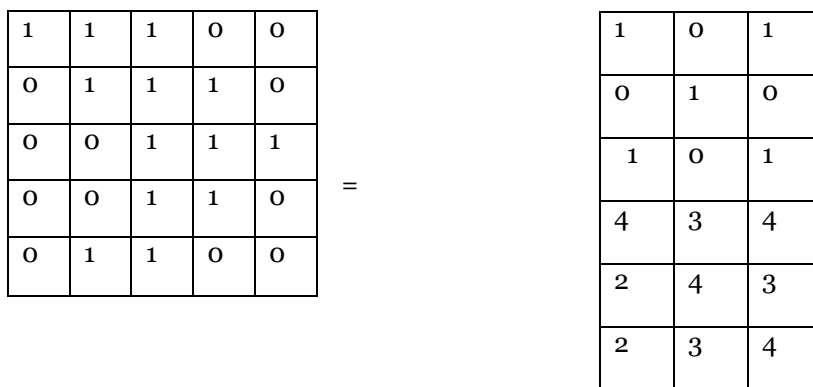
### **1.4. Disease Classification – Optimized Deep Neural Network**

Optimized Deep Neural Network is suitable for eliminating the over fitting and under fitting challenges of the learning model towards disease classification task. In order to estimate the optimal configuration to the disease classification, hyperparameter setting and tuning is established. Optimally

configured layer of the network is processed with optimal features of the metaheuristic optimization to generate the resultant disease classes[20]. Each layer of model is functionalized with activation function to generate the layered results. Hyperparameter tuning is attain linear function to process the feature towards attaining the efficient classification results.

- **Hidden Layer**

The Hidden layer of the deep learning model configuration is composed of the multiple filter or kernel to correlate suitable features on generating the feature map which is considered as classification map on the multiple time intervals of the dataset. Feature map is mathematical process which is operated as combination of the suitable feature vector[21]. Resultant Feature matrix of the metaheuristic process is multiplied with matrix to provide feature map.



**Feature Matrix**

**Kernel Matrix**

**Feature Map**

**Figure 1: Feature map**

The hidden layer yields the disease feature map on the correlation mechanism. Feature map is Converged through proper selection of epoch value and it increase the disease feature extraction on optimizing the activation function through normalization methods[22]. Rectified Linear Unit(ReLU) function is optimized to gather the linear disease feature map[23]. Distance between each feature in the map is estimated on utilizing the cosine distance measure to generate the subset of the feature vector

Feature map is processed using Cosine distance is defined as

$$C_f = x(n^t f^t + R)$$

- **Output Layer**

Output layer of the deep neural network composed of softmax layer, loss layer and activation layer along multiple disease constraints to handle the feature map from the hidden layer. Feature map contains the structured disease feature on basis of its interrelationship to the particular disease characteristics. Discriminative disease feature map related to the heart disease is obtained on processing the temporal features information's such as covid -19 or season disease features.

Connected Hidden layer employs the activation function along feature normalization and feature flattening functions to avoid the non-linearity and over fitting complication in the disease attribute classification[24]. Hidden layer is termed as associated illustration of the disease feature map is depicted in figure 2. Softmax operation to operate classification process is embedded in the output layer to produce the disease classes of heart diseases.

Classifier mentioned in the Softmax operation deduces the feature map into disease class vector. Hidden layers connected verifies the model reliability on basis of the loss function. The loss layer is included in hidden layer connection to reduce the feature differences among features on the heart disease classes using cross entropy function[25].

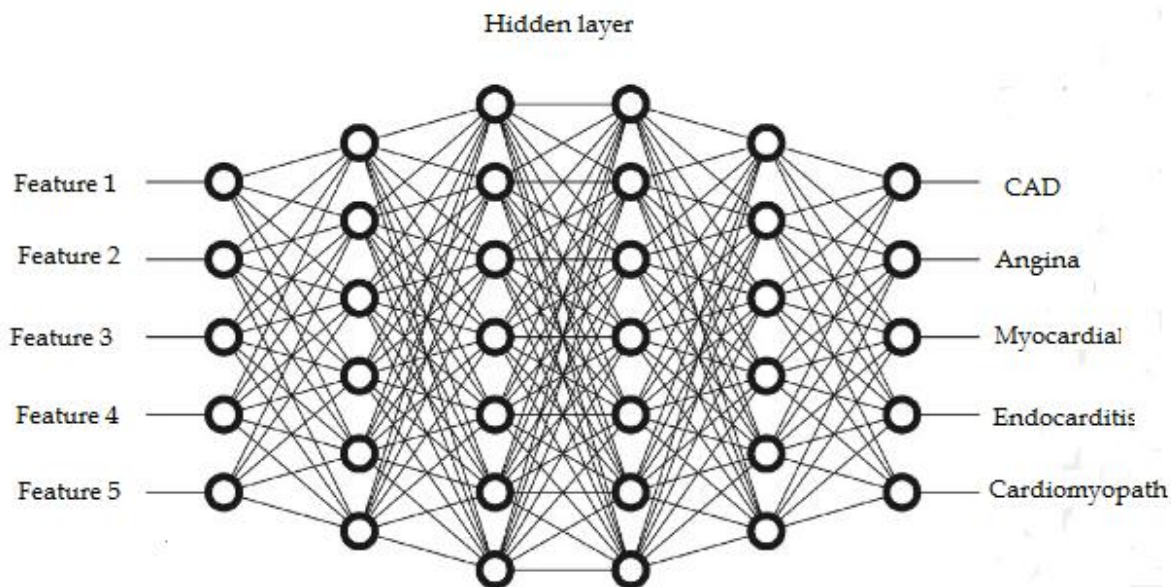


Figure 2: Connected layer of the Deep Neural Network

The final classification result is produced by employing the decision rule of naive Bayes classifier. Table 1 represents the hyper parameter of optimized deep neural network.

Table 41: Hyper Parameter to the Optimized Deep Neural Network

Hyper Parameter	Values
Feature Set Size	254
Learning Rate	0.06
Feature Dimensions	54
Epoch Value	50
Activation Function	ReLu
Optimizer	Gradient descent
Loss function	Cross entropy

### Activation function

Feature weight is used to adjusted to control the learning rate of the current architecture using ReLu function. Optimized Deep Neural Network is modeled on basis of many to one structure through ReLu based activation function. ReLu based activation function[26] is employed to bias the output layer. It is mentioned as represented in the equation 5

$$Y_s = \text{ReLu}(x_s).. \text{Eq.5}$$

It is implemented to analyze the feature and compute the feature for expressing the classes with high level and low level features of the heart diseases[27]. Disease classes contain the long term and short term illness features to the specified comorbidity. Figure 3 mentions the architecture of the current heart disease classification model.

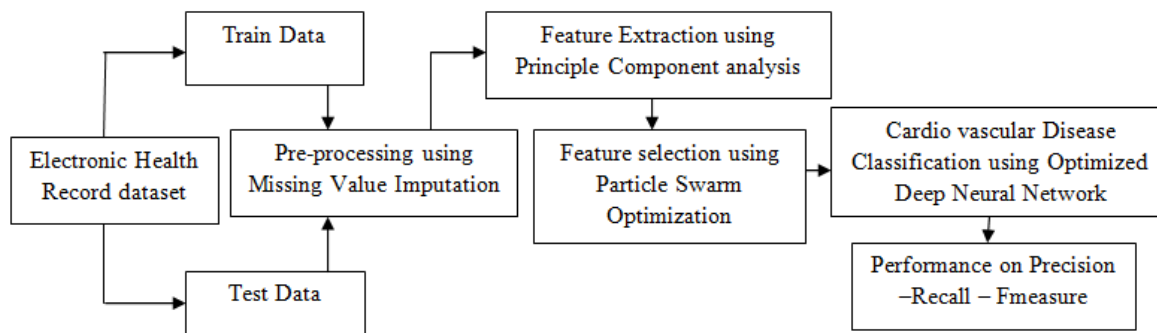


Figure 3: Architecture of Current methodology

- **Loss Layer**

Loss layer is to enhance the classification accuracy of the classification process on employing the cross entropy loss function.

**Algorithm 1: Heart Disease classification**

Input: ORDBA Dataset

Output: Major Heart disease classes

Process

Pre- Process ()

    Compute Missing Attributes ()

        Determine Centroids value to attribute contains missing value on employing KNN

        Allocate the Top Nearest value of computed centroids as Missing Value to particular attribute

    Outlier Attribute Reduction SVD ()

        Dimensionality Reduction to low dimensional attribute from High dimensional attributes

    Feature Extraction PCA ()

        Convert the low dimensional data into data matrix

        Calculate Covariance matrix  $C_m$  and Correlation matrix  $E_m$

        Eigen Vector  $E_v$  is considered as feature set and Eigen Value  $E_v$  as feature

Optimized Deep Neural Network ()

    Hidden layer ()

        Feature Map

        Activation Layer ()

        Allocate ReLU Function to generate class

        Output layer ()

        Naive Bayes Classifier

        Disease Classification- Cardiovascular diseases Classes.

**2. Experimental Results**

The experimental analysis of the current approach is employed on the electronic health record termed as ORDBA which was obtained from UCI machine learning repository. Python programming is designed to model the learning process and pre-processing the dataset. Further dataset is partitioned into training, testing and validation data. Data validation is modeled using multiple fold validation. In

this section, Performance of the optimized deep neural network for heart disease classification has been assessed against convolution neural network.

The Confusion matrix is applied to validation data of the Electronic Health Record dataset to validate the performance of the optimized Deep Neural Network. Confusion Matrix is produced on basis of the specified batch size =128 and epoch =50. This architecture is constructed in Tensor flow backend[26]. The current approaches for heart disease classification is assessed against the following measures Precision, Recall, F1-score [10]

● **Precision**

It is to determine the Positive predictive value on the disease class generated. In other words it considered as ratio of similar attribute instances among the retrieved attribute instance obtained from the resultant feature vector using feature optimization process.

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False Positive}} \dots \text{Eq.6}$$

● **Recall**

It is to determine the significant attribute instance which extracted from the feature vector over the whole amount of relevant attribute instances on the classes including feature instances. The recall measure is mentioned as

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}} \dots \text{Eq.7}$$

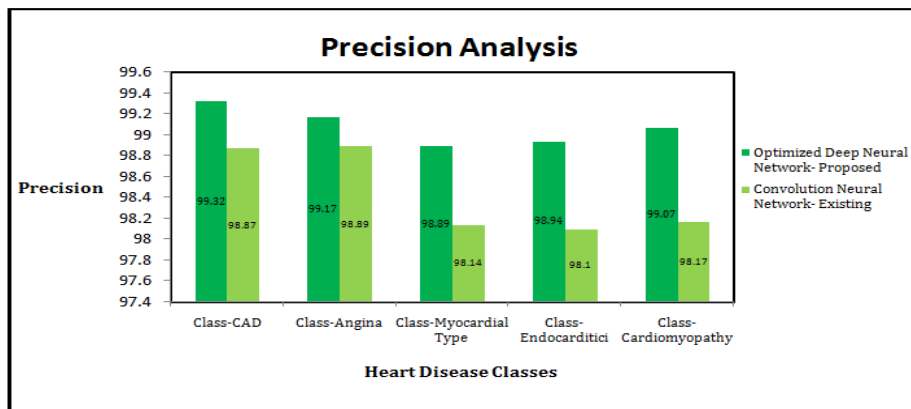
● **F Measure**

It is to estimate the learning model's classification accuracy on processing the high dimensional dataset and is mentioned as the weighted harmonic mean of the precision and recall of the feature instance in the disease feature vector.

F measure is mentioned as

$$\text{F measure} = 2 * \frac{\text{True positive} + \text{True Negative}}{\text{True positive} + \text{True Negative} + \text{false positive} + \text{False negative}} \dots \text{Eq.8}$$

The total number of parameters in this model is 50. The numbers of trainable parameters are 65 and there are no non trainable parameters. The precision of the current optimized deep neural network is depicted in the figure 4



**Figure 4: Performance Analysis of Deep Neural Network against Convolution Neural Network with respect to Precision**

The computation of recall and accuracy on each epoch to the testing and training data of the EHR dataset is computed. The plot of recall for the testing and training instances via optimized deep neural network is depicted in Figure 5 to heart disease classes such as CAD, angina, myocardial type, Endocarditic and Cardiomyopathy[27].

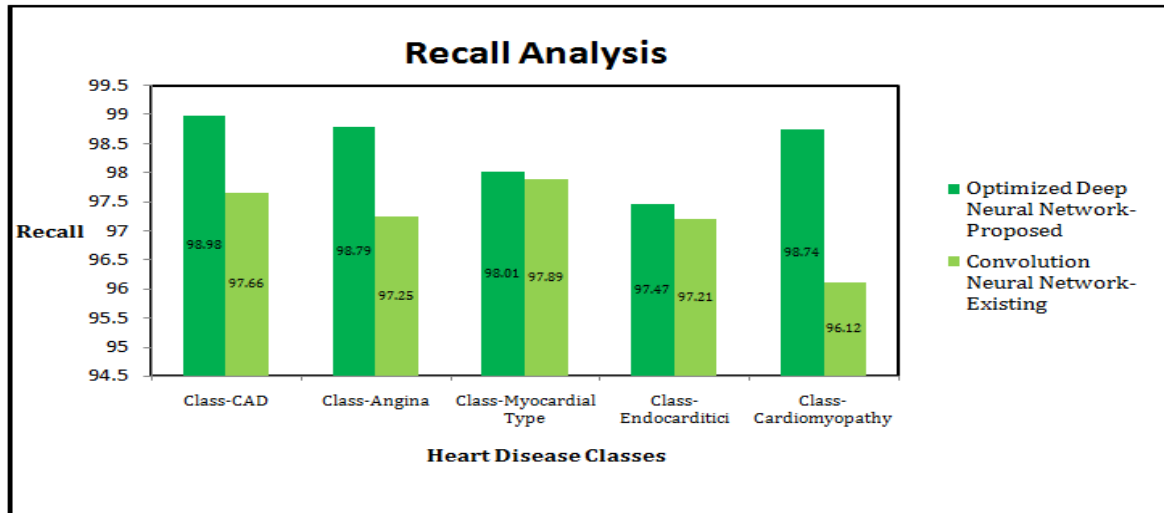


Figure 5: Performance Analysis of Optimized Deep Neural Network against Convolution Neural Network with respect to Recall

Similarly the accuracy for the current optimized deep neural network for testing and training data is computed on setting the epoch value along its varying sizes[28]. The discriminant features to the class are obtained on objective function formation on the analysis on feature space for effective computation for multiple disease classes. In this architecture, dataset is processed to attain the feature space on employing activation function to generates high accuracy.

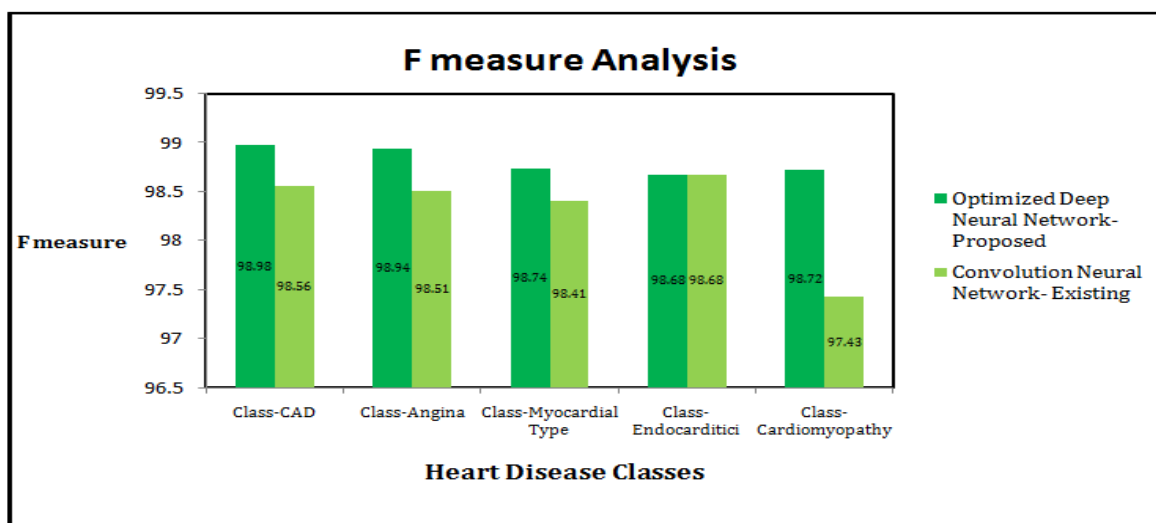


Figure 6: Performance Analysis of Optimized Deep Neural Network against Convolution Neural Network with respect to F measure

The optimized deep neural network model with particle Swarm optimization[29] reduces the complexity and computational time by embedding a local search operation on fine tuning of the hyperparameter of the architecture. Figure 5 mentions the performance accuracy outcomes to optimized deep neural network model. Learning rate[30] is reconstructs the classes on the activation layer of the DNN model.

Posterior distribution of the optimal features to labeled classes is visible on joint configuration of the multiple unit of hyperparameter optimized deep neural network of the current model. Class of Heart disease classes and prognosis of the disease outcome is predicted in this architecture. Table 2 represents the performance of the current deep learning architecture for heart disease classification.

**Table 1: Performance Analysis of Optimized Deep Neural Network against Convolution Neural Network**

<b>Disease Class</b>	<b>Method</b>	<b>Precision</b>	<b>Recall</b>	<b>F measure</b>
Class-CAD	Optimized Deep Neural Network-Proposed	99.32	98.98	98.98
	Convolution Neural Network-Existing	98.87	97.66	98.56
Class-Angina	Optimized Deep Neural Network-Proposed	99.17	98.79	98.94
	Convolution Neural Network-Existing	98.89	97.25	98.51
Class-Myocardial Type	Optimized Deep Neural Network-Proposed	98.89	98.01	98.74
	Convolution Neural Network-Existing	98.14	97.89	98.41
Class-Endocarditic	Optimized Deep Neural Network-Proposed	98.94	97.47	98.68
	Convolution Neural Network-Existing	98.10	97.21	97.78
Class-Cardiomyopathy	Optimized Deep Neural Network-Proposed	99.07	98.74	98.72
	Convolution Neural Network-Existing	98.17	96.12	97.43

### Conclusion

In this article, Optimized Deep Neural Network has designed and implemented for heart disease classification is estimated using electronic health record dataset. In this work, optimization of the deep neural network for disease classification is carried out using Metaheuristic optimization approach represented as particle swarm optimization method. Furthermore current architecture incorporate the hyperparameter tuned deep neural network generate highly accurate disease classes as classification results. Present model is capable of detecting the heart disease in early stages and it is effective in computing disease prognosis stages of the heart patient. Finally proposed optimization technique assist to identify an optimal attribute which is enough to predict heart disease using deep neural network on the various hidden layers of the model.

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