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PARTICLE SWARM OPTIMIZATION ENABLED MULTICLASS CONVOLUTION NEURAL NETWORK FOR CARDIOVASCULAR DISEASE CLASSIFICATION

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ABSTRACT

Cardiovascular disease classification is considered an important concern in the medical research community as heart problems are the growing cause of mortality around the world. Hence automated models for cardiovascular disease classification eliminate the serious complication of the people. Machine learning approaches have been considered to be optimal to classify the diagnosis data of the patient but those models lead to several complex characteristics on processing the disease features and it consumes more time for increasing the accuracy on disease discrimination. In order to mitigate those complications, deep learning architecture is considered to be effective as it operates the complex characteristics in a short span of time. In this paper, a new deep learning model is designed and proposed for cardiovascular disease classification. The design contains a multiclass convolution neural network along Metaheuristics optimization technique termed as particle swarm optimization to discriminate the disease on the basis of the risk level and clinical features of the disease. The preliminary dataset preparation involves filling in missing values within a high-dimensional electronic health dataset. Missing value imputation is employed using the K- Nearest Neighbour method. In many cases, dataset contains irrelevant attributes which leads to high complexity in processing of the architecture, therefore it is eliminated using dimensionality reduction and outlier removal techniques such as matrix factorization or singular value decomposition. Preprocessed data is normalized by incorporating the Z score Normalization technique to enhance the data integrity and uniformity in the attributes. Normalized categorical data is exposed to principle component analysis to extract the distinguishing disease feature. Extracted disease feature is processed with Metaheuristics technique represented as particle swarm optimization to yield optimal disease feature for cardiovascular disease classification. Optimal disease features have been employed in the Multiclass Convolution Neural network for Heart disease classification. In this architecture convolution layer and Max pooling layer has been employed to process the disease feature with kernel setting to produce the feature map. Moreover, sigmoid function is used as activation functions of the CNN layers to increase the classification performance of the model on the

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Vol. 4(1), March 2024, pp. 104-117

training stage in generating disease classes. Experimental analysis has been carried out on employing EHR dataset to evaluate the performance of the proposed discriminative deep learning framework on processing with optimized optimal disease features against the conventional approaches on the multi fold validation. Proposed framework achieves accuracy of 99% on disease classification using PSO when compared against the various optimization techniques.

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

1. INTRODUCTION

Cardiovascular disease is a represented as growing cause of the mortality around the world and especially it become heavily complicated to healthcare industry during covid -19 pandemic. Cardiovascular disease is highly characterized with respect to changes of pressure in the blood flows into vessels and arteries. Especially rheumatic heart disease is considered a major contributing factor for CVD. However other kinds of CVDs result due to other disease comorbidity such as covid -19 inspection reviewing encompasses stroke, aortic aneurysms, peripheral artery disease, thromboembolic disease, and venous thrombosis [1].

Furthermore, the symptoms of cardiovascular diseases are due to variation of multiple health factors of patients along with other diseases such as diabetics, cancer, periodontal diseases. Hence identifying the comorbidity of the disease with cardiovascular disease is highly complex to diagnose. Hence there exists a large requirement in the medical community for automated accurate heart disease diagnosis models on varying health conditions of the patient. Recently Electronic health Records have been considered as medical records containing much information about the patients. It has been exhibited to obtain substantial potential information to provide multiple insights on the research on the diagnosis of the patient's health using EHR data. Electronic Health Records is becoming vital data collection to early diagnosis of disease through data analytics.

Traditionally Cardiovascular disease Classification has been processed in terms of manual and automated diagnosis techniques. However Manual techniques lead to inappropriate detection and irrelevant disease classification. In order to achieve accurate and reliable cardiovascular disease classification [2], big data analytics, artificial intelligence, machine learning and deep learning approaches have to be implemented to generate the accurate outcome [3]. Despite its huge advantage, it faces more complications on processing the EHR type of dataset as it contains a curse of dimensionality and data sparsity issue which makes machine learning approaches inappropriate for disease diagnosis and disease classification. To mitigate above mentioned challenges, a deep learning framework has been designed as a disease classifier to achieve accurate disease classification with following design specification as proposed methodologies.

In this article, Multiclass Neural Network based on Metaheuristics technique termed as particle Swarm algorithm has been implemented to extract the suitable features for effective cardiovascular disease classification. Proposed approach is to categorize the type of heart disease with an enlarged feature set. In this proposed design specification, technique for missing value prediction, data normalization and dimensionality reduction has been included to pre-process the dataset. Preprocessed dataset is applied to the feature extraction process by employing the principle component analysis. Extracted disease features are projected to particle swarm optimization techniques to compute the suitable feature set for classification. It is to model a compact guide regarding constraints and strategies of deep learning processes on the various layers of the convolution neural network for disease classification.

The upcoming section of this article described as follows: section 2 related to the active dataset and architecture of the disease. Section 3 represents the design specification of the proposed architecture to classify the cardiovascular disease on setting the hyperparameter of the activation of the related model to classify the cardiovascular disease. The outcome of the described model is validated and evaluated against the existing approaches using various performance measures that have been mentioned in the section 4 along the benchmark dataset illustration. Finally section 5 summarises the article.

2. RELATED WORK

In this section, detailed analysis of relevant techniques employed for the cardiovascular disease classification employing machine learning classifiers and deep learning classifiers has been investigated with illustrations of the major advantages and challenges.

2.1. Feed Forward Neural Network

In this literature, feed forward neural networks are analysed on the dataset of heart diseases. It belongs to the machine learning paradigm. Feed forward neural process each disease feature as neuron. The neuron will form a network to represent the disease classes. Feed forward neural network considered in this work is a multilayer perceptron neural network. Model is capable of the suitable features on background propagation. Model produces an accuracy of 89.4% as it performs the feature selection on iterations. However it is unsuitable for voluminous data since it can be computationally costlier [4].

2.2. Probabilistic Neural Network

In this literature, cardiovascular disease classification approach is analysed using probabilistic neural networks and dataset such as Cleveland, Hungarian, and Switzerland. The neural network

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Vol. 4(1), March 2024, pp. 104-117

generates the disease classes on the basis of the probability of generating the optimal features for reliable classification. In order to alleviate that misclassification error due to irrelevant features of dataset, sigmoid based activation function has been implemented on transferring the learnt weights from one layer to another on various states to generate diverse classification results with enhanced accuracy [5].

3. PROPOSED MODEL

In this part, a new design architecture entitled as Multiclass Convolution Neural Network which is to diagnose cardiovascular disease and to classify the disease employing Metaheuristics technique termed as particle swarm optimization. The details of each component of the proposed framework to classify the cardiovascular disease is as follows

3.1. Data Preprocessing

A large dimensional medicinal datasets in the form of high dimensional data is highly complex towards data classification. Data Pre-processing has been employed to generate the suitable data format for classification using data cleaning, missing value prediction, data Normalization and dimensionality reduction techniques from reducing the high dimensional data to low dimensional data has been processed to achieve effective disease classes

3.1.1. Missing Value Imputation- K-Neighbour Method

High dimensional medicinal data contain the missing value and it is processed to fill the missing value using the K nearest Neighbour method [6]. It is considered as a data Imputation technique on computing the centroids value to the attribute which has missing value. Centroids criteria employ the Euclidean distance function to impute the missing values of the attribute or variable through relationship among the known attribute value. It is predicted on computation of the centroids for the particular attribute

3.1.2. Data Dimensionality Reduction - Singular Value Decomposition

In this part, Singular Value decomposition technique is employed to transform the high dimensional data to low dimensional data on reducing the irrelevant and outlier attribute of the dataset. It carries linear transformation as it is capable of eliminating the over fitting issues. Initially the data set is represented in the vector space model containing domain adapted parameters [7]. Each Dimension of the dataset is processed from the vector space model applying the data transformation matrix which is as follows

Data transformation Matrix of high dimensional data $T_m = U\sum_{i=0}^{n} V$ Eq.1

Where V is considered as vector Space Representation of the Dataset

U is considered as the Domain Parameter of the Dataset

Data transformation Matrix minimizes the dimensions of the dataset by considering only domain adapted parameters.

3.1.3. Data Normalization – Z Score Normalization

Data normalization is to produce the resultant records with the values of the reduced domain adapted attributes of the value under a specific range method. Z-Score normalization approach is applied on incorporation of the standard deviation and mean measures to normalize (transform or rescale) each input value of the resultant feature vector such that subsequent features have unit variance and a zero mean [8]. Each sample, $X_{i,n}$ in the dataset is varied into $X'_{i,n}$. It is also termed as zero-mean normalization. The normalized feature is represented as

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

Where μ, illustrates the mean and $\sigma_i as$ standard deviation value of ith feature respectively

3.2. Feature Extraction –Principle Component Analysis

Principle Component Analysis [9] is to extract the disease feature from the normalized dataset. Normalized dataset is used in the matrix form. Principle component of the resultant dimensions of the matrix is considered. In those dimensions, the dimension with greatest variability (covariance) of the instances and the dimension with least variability (Correlation) of the instances is collected. In that covariance and correlation matrix, Eigenvectors are derived with eigenvalues. Those eigen vector represent feature and eigenvalue represent the feature set.

Eigenvectors of the feature is termed as $\langle_j = \sum q_j^T x$ where j=1,2,…,m …. Eq.3

EigenValue of the $\langle_j$ contains the principle feature sets is {f1, f2, f3….Fn}

3.3. Feature Selection using Particle Swarm Optimization

Particle Swarm Optimization considered as Metaheuristics optimization is employed to derive the optimal features of the principle features extracted from PCA technique. PSO outcomes the suitable feature of cardiovascular disease classification. In PSO, particle and velocity representation and fitness computation is processed using the weights of the features on the various heuristic conditions. Fitness function for the particle swarm optimization is given as

Fitness function = Maximum (features on particular heuristics)

Suitable feature is computed using

$$V = v = v + w_1 * rand * (LBest - p) + w_2 * rand * (gBest - p) \quad \text{...} \quad \text{Eq.4}$$

Where V is the fitness feature selected for classification process

P is the particle or suitable feature

W1 and W2 is considered as weight of the feature in the particular vector

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Vol. 4(1), March 2024, pp. 104-117

3.4. Disease Classification – Multiclass Convolution Neural Network

Convolution Neural Network is capable of eliminating the overfitting and underfitting issue of the learning model towards classification tasks. In order to compute the optimal configuration to the disease classification, hyperparameter setting and tuning is carried out. Optimally configured layer of the network is processed with suitable features of the Metaheuristics optimization to produce the resultant disease classes. Each layer of the model is functionalized with activation functions to produce the layered outcomes. Hyperparameter tuning is achieved by gradient function to process the feature towards achieving the effective classification results.

- **Convolution Layer**

Convolution is a mathematical process which is operated as a combination of the suitable feature vector and filter. The Resultant Feature matrix of the Metaheuristics process is multiplied with kernel matrix to provide convolution matrix or feature map.

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Suitable Feature Matrix

1	0	1
0	1	0
1	0	1

Kernel Matrix

=

4	3	4
2	4	3
2	3	4

Feature Map

Figure 1: Feature map of multiclass Convolution Neural Network

The convolution layer yields the disease feature map on the convolution operations. Convergence of the feature map is carried out using epoch and it enhances the disease feature extraction on normalization of the activation function using ReLu function to extract the linear feature map. Distance among each feature in the map is estimated using cosine distance measure to produce subset of the feature vector

Cosine distance of the features in the feature map is computed as

$$C_f = y(m^t f^t + c)$$

- **Fully Connected Layer**

Fully connected layers of the CNN are organized with softmax layer, loss layer and drop out layer along various constraints to process the feature map from the convolution layer. Feature map contains the structured disease feature on the basis of its interrelationship to the particular disease characteristics. Discriminative feature map also contains the temporal features information such as covid -19 or season disease features.

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Vol. 4(1), March 2024, pp. 104-117

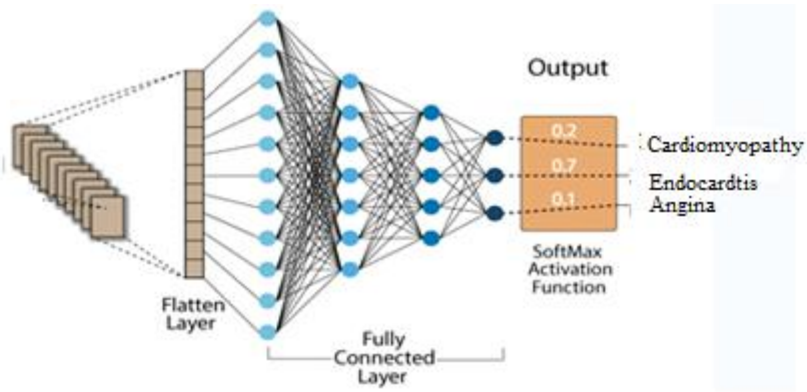

Figure 2: Fully connected layer of the multiclass Convolution Neural Network

Fully connected layers use the activation function to process feature normalization or feature flattening as a layer to eliminate the non-linearity and over-fitting issues in the feature classification. Fully connected representation of the feature map is represented in the figure 2. Softmax layer contains the classifier process and is represented in the fully connected layer to produce the disease classes of cardiovascular diseases.

Classifier in the Softmax layer deduces the feature map into disease class vectors. Fully connected layers verify the reliability of the model on the basis of the loss function. The loss layer is incorporated in a fully connected layer to minimize the feature variance on the disease classes using cross entropy function. The closest approximation of the testing sample may be from various classes, which represents that the minimal residual may be derived from numerous classes. The final classification result is generated by integrating the results based on the voting rule.

The class coefficients for the suitable disease feature is given by class objective function as

$$Y = \beta_0 + \beta_1 X$$

Where the class coefficients are represented as

$$\beta_1 = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2}$$

The class objective function modelled with incorporation of the class coefficients to estimate the Error Sum of Square (SSE). SSE is used to design the drop constraints in the drop layers. Drop constraints the temporal features of the patients. Dropout layer eliminates the temporal feature on the high level feature processing. Finally it determines the multiple linear weights of high level features and low level feature diseases. In addition, feature weight can be computed through iterations.

$$\Delta W_i = C(t\text{-}net)x_i$$

where ***'c'*** is the learning rate

'x' is input for that weight

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Vol. 4(1), March 2024, pp. 104-117

On the objective of minimizing the SSE and solving loss of the classifier, Delta rule will be updated. Algorithm 1 explains the working of the proposed disease classification model. Table 1 represents the hyper parameter of multiclass convolution Neural Network.

Table 1: Hyper Parameter to the Multiclass Convolution Neural Network

Hyper Parameter	Values
Feature Set Size	214
Learning Rate	0.03
Feature Dimensions	45
Epoch Value	45
Activation Function	ReLu
Optimizer	Gradient descent
Loss function	Cross entropy

- **Activation function**

Thus, the learning rate of the proposed architecture has been controlled and adjusted with the weights on the features using sigmoid function. The activation function of Multiclass convolution Neural Network is illustrated in form of many to one structure through sigmoid function. The activation function is implemented to bias the output layer. It is represented as follows

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

It is employed to analyze the feature and determine the feature for expressing the classes with high level and low level features of the cardiovascular diseases. Disease classes contain the long term and short term illness features to the specified comorbidity. Figure 1 represents the architecture of the proposed model.

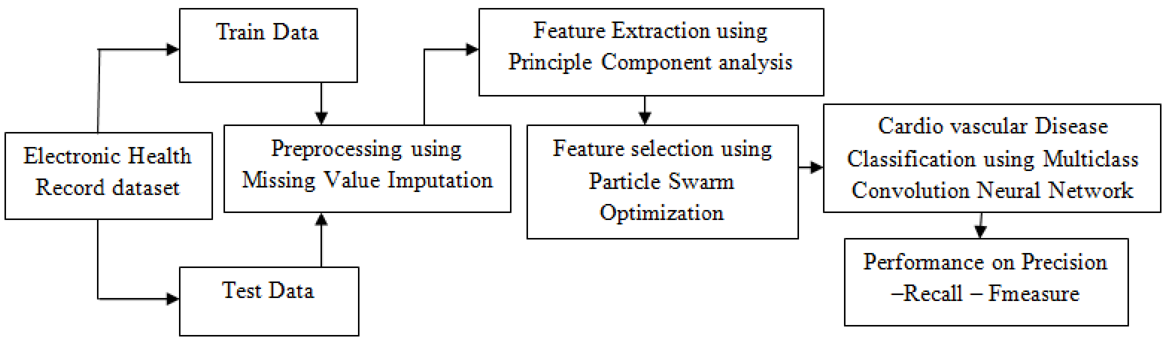

Figure 3: Architecture of proposed methodology

- **Loss Layer**

This layer is to increase the classification accuracy of the classification process on employing the cross entropy loss function.

Algorithm 1: Cardiovascular Disease classification

Input: EHR Dataset

Output: Heart disease classes

Process

Pre- Process ()

Compute Missing Attributes ()

Estimate the attribute Centroids value using KNN

Allocate the Nearest value of centroids as Missing Value to missing attribute

Feature Reduction SVD ()

Transform High dimension to Low dimension

Feature Extraction PCA ()

Determine the Covariance matrix C_m

Determine the Correlation matrix

Eigen Vector E_v as feature and Eigen Value E_v as feature set

Multiclass Convolution Neural Network ()

Convolution layer ()

Compute feature Map

Activation Layer ()

Allocate Sigmoid Function to generate class

Fully connected layer ()

Softmax layer ()

Random Forest Classifier

Loss layer ()

Cross Entropy Layer ()

Dropout layer ()

Output Layer ()

Disease Classification- Cardiovascular diseases Classes.

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Vol. 4(1), March 2024, pp. 104-117

4. Experimental Results

The experimental analysis of the proposed approach is carried out in the electronic health record which was obtained from UCI machine learning repository. Python programming is designed to model the learning model and preprocess the dataset. Further dataset is partitioned into training, testing and validation data. Data validation is employed using multiple fold validation. In this section, Performance of the proposed convolution neural network for cardiovascular disease classification has been evaluated against convolution neural network.

The Confusion matrix to validate the performance of the proposed recurrent neural network is on the validation set of the dataset. The Confusion Matrix is generated by examining batch size =128 and epoch =50, the Simple RNN model is fitted using Tensor flow backend. The proposed approaches for disease classification is evaluated against the following measures Precision, Recall, F1-score [10]

- **Precision**

It is to estimate the Positive predictive value on the class also represented as ratio of similar feature instances among the retrieved feature instances obtained from the resultant suitable feature vector using Metaheuristics optimization process.

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

- **Recall**

It is estimated the relevant similar feature instance which is retrieved from the feature vector over the total amount of relevant instances on the classes composing feature instances. The recall is computed as

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

- **F Measure**

It is a compute the classification accuracy of the high dimensional data and is defined as the weighted harmonic mean of the precision and recall of the feature instance in the feature vector.

F measure is provided by

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

The total number of parameters in this model is 45. The numbers of trainable parameters are 65 and there are no non trainable parameters. The precision of the proposed MCNN model is illustrated in the figure 4.

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Vol. 4(1), March 2024, pp. 104-117

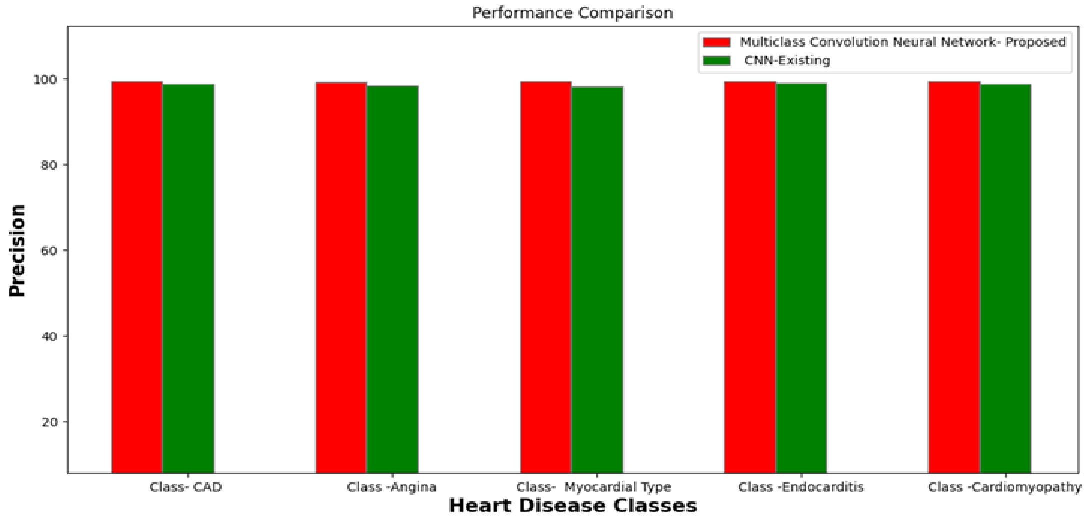

Figure 4: Performance Analysis of Multiclass Convolution Neural Network against Convolution Neural Network with respect to Precision

The computation of recall and accuracy on each epoch to the testing and training data is computed. The plot of recall for the testing and training instances via MCNN is illustrated in Figure 5 to cardiovascular disease classes such as CAD, angina, myocardial type, Endocarditis and Cardiomyopathy.

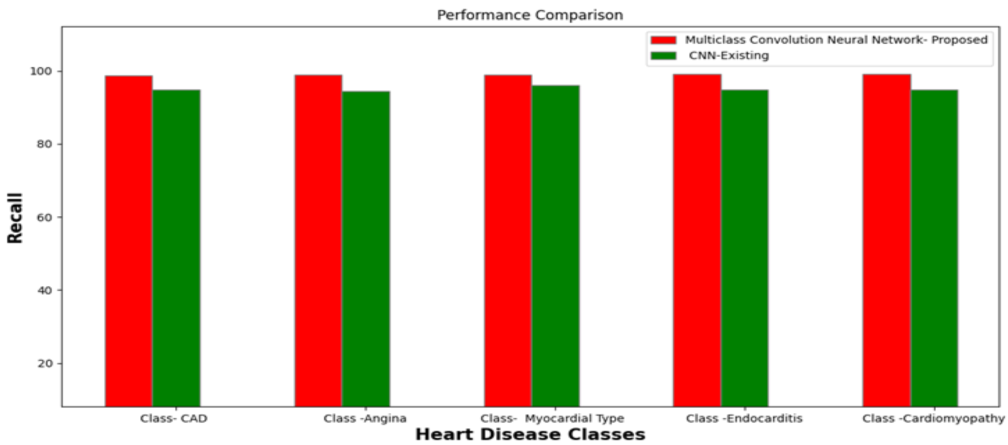

Figure 5: Performance Analysis of Multiclass Convolution Neural Network against Convolution Neural Network with respect to Recall

Similarly the accuracy for the proposed MCNN for testing and training data, epoch is set along changing sizes. The discriminatory features to the class are obtained on objective function formation on the analysis on feature space for effective computation for various disease classes. In this model, dataset is processed to obtain the feature space by employing objective function to yield high accuracy.

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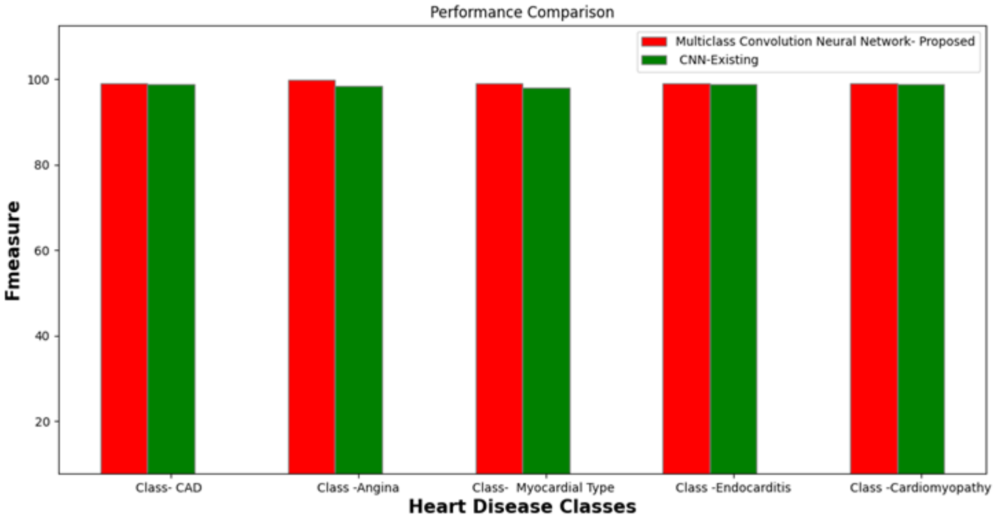

Figure 6: Performance Analysis of Multiclass Convolution Neural Network against Convolution Neural Network with respect to F measure

The MCNN model with particle Swarm optimization reduces the complexity and computational time by embedding a local search operation on fine tuning of the hyperparameter of the model. Figure 5 represents the performance of the accuracy for the MCNN model. Learning rate reconstructs the classes on the activation layer of the CNN model.

Posterior distribution of the optimal features to labelled classes is visible on joint configuration of the various units of MCNN in the network. Class of cardiovascular disease also predicts the prognosis of the disease outcome. Table 2 shows the performance of the proposed model for cardiovascular disease classification.

Table 2: Performance Analysis of Multiclass Convolution Neural Network against Convolution Neural Network

Disease Class	Method	Precision	Recall	F measure
Class-CAD	Multiclass Convolution Neural Network – Proposed	99.41	98.78	99.12
	Convolution Neural Network-Existing	98.77	94.66	98.58
Class-Angina	Multiclass Convolution Neural Network – Proposed	99.28	98.89	98.98
	Convolution Neural Network – Existing	98.49	94.25	98.51
Class-	Multiclass Convolution Neural	99.42	99.01	99.12

Myocardial Type	Network – Proposed			
	Convolution Neural Network – Existing	98.12	98.79	98.88
Class-Endocarditis	Multiclass Convolution Neural Network – Proposed	99.34	99.06	99.24
	Convolution Neural Network – Existing	98.94	94.27	98.66
Class-Cardiomyopathy	Multiclass Convolution Neural Network – Proposed	99.41	99.12	99.33
	Convolution Neural Network – Existing	98.89	94.29	98.69

Conclusion

In this paper, Multiclass Convolution Neural Network has been designed and implemented for cardiovascular disease classification on evaluating the model using electronic health record dataset. In this work, optimization of the neural network for disease classification is carried out using Metaheuristics optimization technique termed as particle swarm optimization algorithm. Furthermore, the proposed approach employs the convolution neural network in this work to yield the high accurate classification results. Proposed model is capable of detecting the disease in early stages and it is effective in determining prognostic stages of the patient. The proposed optimization helps to identify an optimal attribute which is enough to predict cardiovascular disease using convolution neural networks on the various layers of the model.

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