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ECG BASED MULTI MODAL FRAMEWORK FOR HEART DISEASE DETECTION

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ABSTRACT

Most severe diseases afflicting the human race is as heart disease, so early diagnose and prediction of heart disease is necessary to save human life. Heart disease requires early diagnosis and prognosis in order to save lives. Thus the accurate prediction is done by using deep learning algorithms to avoid the disadvantages in machine learning because which use separate algorithm for feature selection to extract feature. As a result, Convolutional Neural Network (CNN) combined with Aquila Optimization Algorithm (AOA), as Hybrid Deep Convolutional Neural Network (DCNN), which is employed to detect the heart. The AOA algorithm is used to select the weight parameters in the DCNN, which works well on images. Electrocardiogram (ECG) images are used for predicting of cardiovascular disease. The concept driving this study is to combine ECG images as well as clinical data in order to give high performance in prediction. ECG images are pre-processed to scale down the size and then CNN is applied and prediction is done. In this case, different methods for pre processing are applied and best pre-processing method is found in this work. ECG images are taken and different mathematical methods like Fourier transform, DCT or combination of Fourier transform and DCT etc are applied and best method is found. The proposed model is then implemented in MATLAB, and its performance is assessed by comparing it to other existing CNN models.

Keywords: *Deep Convolutional Neural Network, Aquila Optimization Algorithm, Heart Disease, Electrocardiogram, Pre-processing*

1. INTRODUCTION

Heart disease affects the normal heart functioning, resulting in death and severe disorders [1]. Blood vessel diseases fall under the category of heart disease [2]. Another name for heart disease Cardiovascular disease, which impairs heart function by clogging or narrowing blood vessels, causes a stroke, heart attack or chest pain [3]. A few problems of heart also lead to some problems such as heart's muscle, valves or rhythm affected [4]. Heart diseases prediction is the most critical task to detect the type of heart disease at the early stage accurately with the usage of ECG and clinical data. Because of large collection of data, data mining technique make the decision for predicting heart disease [5, 6]. Compared to other chronic disease like cancer, diabetics most of the deaths are caused due to heart related issues [7, 8]. So early diagnose and prediction of heart disease is necessary to save human life. Thus, the accurate prediction is done by using deep learning algorithms to avoid the disadvantages in machine learning because which use separate algorithm for feature selection to extract feature [9].

Researchers studied many approaches for automated cardiovascular disease detection utilizing machine and deep-learning algorithms, frequently employing ECG with amplitude data in one or two dimensional voltages as time-series signal source. Different techniques are studied to categorize ECG signals into time series and demonstrate a significant outcome. Ubeyli [10] utilized its own vector technique for the extracting features and classification of ECG beats. Sharma et al. [11] utilized ECG signals relying on frequency, to diagnose a cardiovascular issue and to obtain the attribute of the Hankel matrix and Hilbert.

CNN offers a variety of benefits over standard biomedical categorization approaches. For instance, they are extensively employed in the detection of cancer of the skin, the categorization of animal behavior [12] the prediction of protein structures and the classification of signal Electromyography (EMG). Moreover, ECG categorization was also

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employed by CNNs. Kiranyaz et al. [13] for particular, proposed a one-dimensional (1D) CNN for real-time ECG-specific patient classification. CNNs are a kind of neural network that incorporates a grid-like data-handling architecture that combines neighboring values, such as those in a two-dimensional (2D) picture.

The main intention of our work is to predict heart disease with high accuracy so that the proposed system can be used in hospitals. Death rate due to heart related diseases can be reduced when the system uses deep learning algorithms. The proposed system uses modified CNN which works well on images. Most of the researchers have done their work on clinical data for accurate prediction like age, gender, BP, diabetics etc [14]. Similarly, ECG images are utilized for forecasting heart disease [15]. To combine ECG images as well as clinical data in order to give high performance in prediction [16]. ECG images are pre-processed to scale down the size and then CNN is applied and prediction is done. In this case, different methods for preprocessing are applied and best pre-processing method is found in this work [17]. ECG images are taken and different mathematical methods like Fourier transform, DCT or combination of Fourier transform and DCT etc are applied and best method is found. Also, instead of using traditional CNN, modified CNN algorithm is applied and hence need to prove that when applying new CNN, the model gives more performance [18].

The performance of proposed system is calculated and analyzed based on the physionet dataset [19]. ECG image to prediction algorithm, as it needs less number of neurons and less number of layers. Along with ECG images when clinical features like age, gender, weight etc is fed to prediction algorithm, the model will give very high accuracy, as each clinical features contributes as an additional parameter to the increase in performance of the model. So doctors can use this model to accurately predict heart disease in hospitals.

The structure of this paper is as follows. In section 2 explains the projected algorithms that are being studied. The proposed systems architecture explains in section 3, the brief details of proposed system performance in section 4, Section 5 experiments with the system's simulation results, and Section 6 concludes the proposed system.

2. LITERATURE SURVEY

Most of the image processing applications use CNN classifier to classify the expected output and the accuracy rate is also high of the image processing system while using this classifier. Some of the CNN applied works are reviewed as follows.

Raimundo F. Pinto et al. [20] have suggested a technique with CNN algorithm for recognizing gestures which involved the steps as morphological filter, generation of contour, approximation of polygon and segmentation of input these were focusing to the accurate extraction of features. The CNN was trained with the created data and then it was processed with trained and tested data. This training and testing was performed by using different CNN.

Gagandeep Kaur et al. [21] have suggested achieving better recognition of occluded images because this world suffered lot from COVID-19 so that the government expects to wear mask to safeguard against covid-19 which was difficult to recognize the whole image. This technique recognized the image in a video frame accurately and CNN identify the image without over-fitting value using optimal parameter values.

Behrouz Rostami et al. [22] have developed technology to assist the wound specialist for easily diagnose with high accurate classifier with less cost and less time because, acute and chronic wounds endanger people's lives. It also aided clinicians in determining the best treatment method by categorising wounds. Deep Learning (DL) and Machine Learning (ML) techniques were utilized for classification, and a DCNN-based classifier classified the wound as surgical, diabetic, or venous ulcers.

Rafid Mostafiz et al. [23] have developed a technology to diagnose diseases and making decisions to help the medical experts. This sparked the idea of using DCNN and chest X-ray images to detect based on discrete wavelet transform (DWT) Covid-19. Initially the image was given for pre-processing by enhancement and segmentation after that the features of DCNN and DWT were extracted.

Iana S.Polonskaia et al. [24] have proposed the automated evolutionary approach FEDOT-NAS for developing the CNN. The object recognition was

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based on the sensing remotely. The major satellite-related datasets were used in the technique of comparing neural structure with that technique. The suggested technique of FEDOT-NAS was a open source available.

S.Irin Sherly et al. [25] presented different filtering methods to improve signal quality in ECG. The performance of different filters were assessed using signal to noise ratios. They found that all denoising techniques are applied in accordance with their level for different types of noise, noise level, and signal length.

Savita Ahlawat et al. [26] have investigated the handwriting detection technique using a CNN is combined with Support Vector Machine (SVM), with both classifier features enclosed. CNN is a feature extractor that automatically extracts features, and SVM is a binary classifier. The handwritten MNIST dataset digits, which were highly distorted and diverse, were used for data training and testing. The CNN differentiate the most common features of handwrites from the images.

S.Irin Sherly et al. [27] proposed an improved ensemble based prediction model for diagnosing heart disease. They have used data from four different databases namely Cleveland, Hungary, Switzerland, and Long Beach. Totally 920 records with 14 clinical features were used for their study. KNN, Random Forest, SVM, Logistic Regression, Bagging DT, Gradient boosting DT were examined on the data and proved Gradient boosting Decision Tree achieved 99.12% accuracy.

Ce Zhang et al. [28] have presented the contextual based deep architecture of CNN and Multi Layer Perceptron (MLP) based pixel was accurately suggested in that technique. These two techniques are developed for classification based on the rule based fusion approach even the two algorithms had two different features of remotely sensed.

S.Irin Sherly et al. [29] presented Honey badger based Faster RCNN for heart failure prediction using ECG signals. The data used for this study were obtained from BIDMC Congestive Heart Failure data set and MIT BIH Normal Sinus Rhythm Dataset. ECG signals were preprocessed using Delayed Normalized Least Mean Square method to remove different noise artifacts. Their model offered an accuracy of 99%, 100% and 98% for the Cardiac Arrhythmia, Congestive Heart Failure and Normal Sinus Rhythm classes in MIT-BIH dataset and 98% and 97% accuracy for CHF severe and CHF normal in BIDMC dataset.

While conducting various studies related to this work, the previous methods have significant drawbacks due to the accuracy and lack of efficient classification of this heart disease.

While predicting the disease the false predictions are largely obtained by previous technique.Deep learning techniques replaced the place of machine learning technique because while using the machine learning techniques the computation time is high.

The error rate also increased due to the false predictions which will lead to inaccurate system. Training to the classifier take long time will slow down the process of the system.

3. PROPOSED PREDICTION SYSTEM

Heart disease refers to any disease that affects the heart, which is the main organ responsible for accurate blood circulation in the human body. There are numerous types of heart diseases caused by irregular blood circulation, high blood pressure, high blood cholesterol, and smoking, among other factors. There are many factors related to each other to cause heart diseases which leads to detect multi-layered problem because inefficient heart disease detection will cause false assumptions associated with unpredictable effects [30]. Therefore, to help the physicians an intelligent diagnostic tool is developed in data mining field with accurate and efficient diagnosis of heart disease with medical care of heart disease.

The proposed work is analysed using electrocardiogram (ECG) data from a patient, and these data are pre-processed to remove noise using filters. The data is then classified using CNN, and the neural network is trained using the proposed dataset. The CNN performance is improved by selecting weight parameters with the help of optimization algorithm of AOA. Figure 1 depicts the proposed system structure. The proposed system's processing steps are described in the sections below.

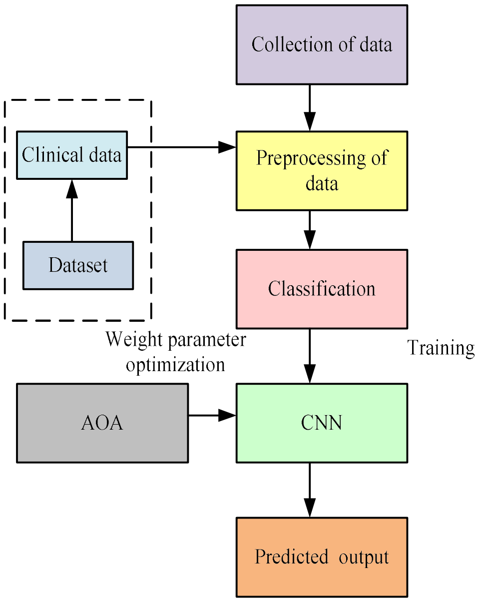

Figure 1: Flow diagram of proposed system

3.1 Input data from ECG of patients

ECG is an electronic device used for analyzing the activity of heart by the process of Electrocardiography. It graphs the electrical activity of the heart with the relationship between voltage and time. By implanting sensors in the human body, the electrical signal of the heart is extracted. During each cardiac cycle, these electrodes detect the small electrical changes caused by cardiac muscle depolarization and repolarization (heartbeat). Normal cardiac cycle pattern changes cause cardiac rhythm disturbances like atrial fibrillation and ventricular tachycardia, insufficient coronary artery blood flow like myocardial ischemia and myocardial infarction, and electrolyte disturbances like hypokalemia and hyperkalemia.

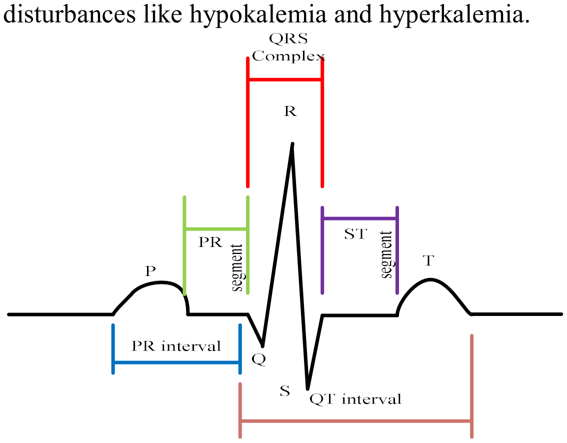

Figure 2: ECG signal

Figure 2 shows an analysis of the ECG signal from the 12 lead electrodes. As a result, the monitoring system records the electrical activity of the heart. The 12 lead ECG with ten electrodes is placed on the patient's limb and on the patient's chest [31]. These electrodes measure the potential magnitude of heart pulses from 12 leads, and these pulses are recorded every 10 seconds. An ECG has three major components, which are as follows:

P wave: Atrioventricular depolarization
QRS complex: The ventricles depolarize.
T wave: repolarisation of the ventricles.

The above figure shows the normal ECG signal, if any changes in the normal signal of ECG the signal is considered to identify the type of disease affected in the heart. The interval of three components is described deeply in table 1. Output of ECG signal is given to the pre-processing phase which is explained as below.

Table 1: ECG signal components and its duration.

ECG components	Description	Duration
P wave	It represents the atria's depolarization. Atrial depolarization progresses from the right to the left atrium.	<80ms
PR interval	This is calculated from the start of the P wave to the start of the QRS complex.	120-200ms
QRS complex	The right and left ventricles rapid depolarization creates QRS complex. This complex has high amplitude when compared to P wave because ventricles have a	80-100ms

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	greater muscle mass than atria.	
J joint	This joint is made between ending of QRS complex and starting of ST segment.	-
ST segment	It is the representation of the period of ventricle depolarization that occurs between the QRS complex and the T wave.	-
T wave	The T wave represents ventricle repolarisation.	160ms
QT interval	The QT interval is the time between the start of the QRS complex and the end of the T wave. Because acceptable ranges vary according to heart rate, it must be corrected to the QT complex by dividing by the square root of the PR interval.	<440ms

3.2. ECG signal noise removal using Pre-processing

ECG signal is the input of the proposed system which is not directly applied for classification because it can be contaminated by a variety of noises with varying properties. Some artifacts are caused by stationary sources, while others are non-stationary and time-varying phenomena. The presence of noise and its ratio to the ECG signal in these artifacts is variable and difficult to predict over time. This will add to the input signal and produce inaccurate output [32]. There are many types of noises in the ECG signals; some of the most affected noises are Baseline wander, Power line interference and Motion artifacts.

3.2.1 Baseline wander

It is a type of noise caused by improper electrode placement in the human body, such as patient movement, respiration, and so on. It has a frequency content is 0.5 Hz. Figure 3 depicts the FIR filter block diagram.

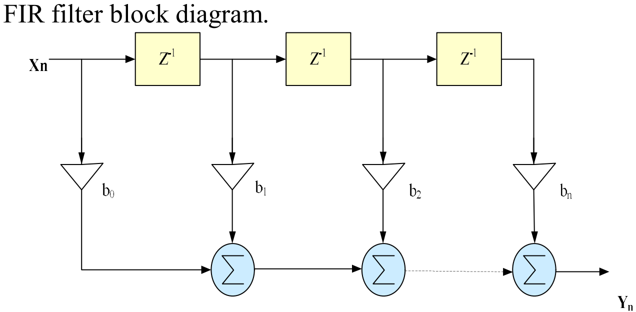

Figure 3: Block diagram of FIR filter

The frequency content is increased during exercise or stress of high movement of body. Because the baseline signal is low in frequency, Finite Impulse Response (FIR) high-pass zero phases forward-backward filtering with a cut-off frequency of 0.5 Hz is used to estimate and remove it from the ECG signal. The filter is designed using a straightforward approach, as shown in the equation (1),

$$H\left(e^{j\omega}\right)=\begin{cases}0, & 0<|\omega|<\omega_c \\ 1, & \omega_c<|\omega|<\pi\end{cases} \quad (1)$$

Where, , fc is cut of frequency of 0.002Hz and the corresponding impulse response is expressed in equation (2),

$$h(n)=\frac{1}{2\pi}\int_{\omega_c}^{\pi} e^{j\omega n}\,d\omega+\frac{1}{2\pi}\int_{-\omega_c}^{-\pi} e^{j\omega n}\,d\omega=\begin{cases}1-\dfrac{\omega_c}{\pi}, & n=0 \\ -\dfrac{\sin(\omega_c n)}{\pi n}, & n=\pm1,\pm2,..\end{cases}$$

(2)

Truncation is done by rectangular windows function is multiplied with h(n) which is shown in equation (3),

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$$h(n) = \begin{cases} 1, & |n| = 0,..,L_c \\ 0, & Otherwise \end{cases} \quad (3)$$

A reasonable trade-off achieve between stop band attenuation and transition band width, a FIR filter should have an order 2L+1 of around 1150.

3.2.2. Interference of Power line

In power lines the noise is caused by electromagnetic fields. It is characterized by 50 or 60 Hz sinusoidal interference was removed from ECG signals as it completely superimposes low frequency [34]. T and P waves in an ECG signal are typically affected by power line interference, which is removed using an Infinite Impulse response (IIR) filter. Figure 4 depicts the IIR filter block diagram.

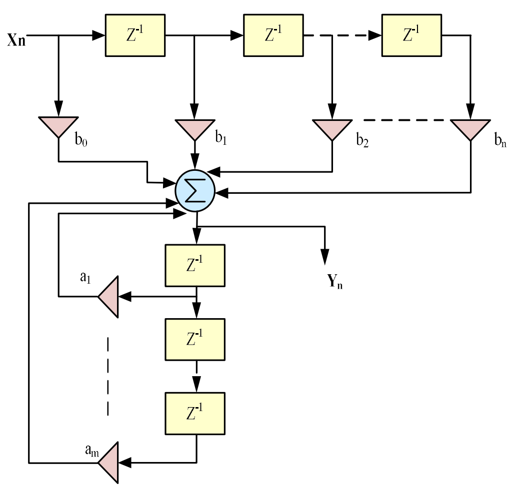

Figure 4: The IIR filter architecture

The IIR filter transfer function is expressed in equation (4),

$$H(Z) = \frac{(1 - Z_1 Z^{-1})(1 - Z_2 Z^{-1})}{(1 - P_1 Z^{-1})(1 - P_2 Z^{-1})} \quad (4)$$

Where, Z is the impulse response.

4.2.3. Motion artifacts.

This noise is created by the stretching of skin around the placement of electrode which changes the electrode's impedance Motion artifacts are similar to baseline wander signal characteristics, but more difficult for combating because their spectral substance appreciably overlaps to the PQRST complex. The most common value is between 1 and 10 Hz. This is removed by IIR and FIR filter. The output of FIR and IIR filters are expressed in equations (5, 6),

$$y(n) = \sum_{n=0}^{N-1} h(n) x(r - n) \quad (5)$$

Here, the filter length is N and x is the input.

$$y(n) = \sum_{n=0}^{\alpha} h(n) x(r - n) \quad (6)$$

3.3. Classification based on CNN using trained data of physionet dataset

This is a type of classifier that classifies the required data from the trained dataset and is widely used in many applications to reduce the number of neural networks used. Figure 5 depicts the DCNN structure.

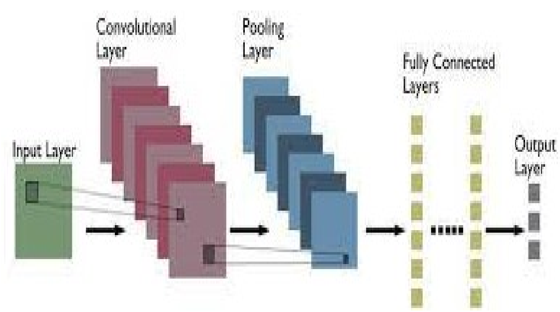

Figure 5: Structure of DCNN

3.3.1. Convolutional layer

This layer serves as a feature extractor, extracting features from the segmented image, which are then mapped by neurons in the form of a feature map. Every neuron in this network is interconnected together and these neurons are trained by weights [35]. The feature map is measured by applying convolution to the input and output. The convolution of input and weight is conveying through a non linear activation function. The neurons consist of weights that are conditioned to be equal. Different weights are corresponding to different feature map thus the features are extracted at every location. The convolutional filter detects image features by taking advantage of weights and multiplying them by the neural network input. Kernels or filters are applied to the images multiple times during this multiplication process, with the kernel applied for 2D structures and the filter applied for 3D structures. These multiplied values are added to determine the filter position.

Generally, the convolution is applied to two functions which are expressed in equation (7). The two function f and g at the time interval of [0, t].

$$[f * g](t) = \int g(t - \tau) f(\tau) d\tau \quad (7)$$

Where, the convolution of f and g is[f*g](t).

The size of the image after convolution is computed using equation (8) and the output is expressed in equation (9),

$$\frac{W - f + 2p}{s} + 1 \quad (8)$$

Where, s is stride and p is padding.

$$Y_i = b_i + \sum_{x_i \varepsilon X} w_{ij} * x_i \quad (9)$$

Where, is the output, i=1, 2,..., D is the depth of the convolutional layer, xi is the input and is the weight parameter.

3.3.2. Pooling layer

The image size is reduced by this layer for maintaining the important features which also reduce the over fitting by decreasing the parameters. The iteration of the convolutional and pooling layers is still ongoing. The fully connected layer output is given to at end of this. The maximum pooling is calculated by below equation (10),

$$\frac{I + 2p - 2}{s} + 1 \quad (10)$$

where, stride is s, padding is p and the image size is I.

3.3.3. Fully connected layer

It connect the neuron in one layer to another layer which is used for classify the image from the flattened matrix. The input vector of flattened pixels is received by this layer Fully connected layers which is filtered by convolutional and pooling layer.

3.4. Weight parameter optimization of CNN using AOA

The hyper parameter in DCNN is optimized using AOA and the structure of AOA is shown in figure 6 which is population based method [36]. The hunting behavior of Aquila is analyzed in this algorithm.

The attacking strategy of Aquila is in four ways to catch the prey. In first strategy, at high altitude Aquila flies highly in the sky for searching the prey and find the prey. If it found the target, it would fly vertical direction and the behaviour of Aquila is expressed in equation (11),

$$X(t+1) = \left(1 - \frac{t}{T}\right) \times X_{best}(t) + \left(X_M(t) - rand \times X_{best}(t)\right) \quad (11)$$

Here, at the t+ 1 iteration the position of individuals are represented as X(t+1), best position at tth iteration is denoted as X best (t), current iteration and maximum iteration is denoted as t and T. At current iteration mean position is denoted as XM (t) and the random number lies between 0 and 1.

In second scheme, at high altitude Aquila will switch from flying to floating on the prey head and the updated position is expressed in equation (12),

$$X(t+1) = LF(D) \times X_{best}(t) + rand \times (y - x) + X_R(t) \quad (12)$$

Where, random position of Aquila is denoted as XR (t), and size of the dimension is represented as D. LF stands for Levy flight function. The shape of the search is denoted as y and x which can be expressed in equation (13),

$$x = (r_1 + 0.00565 \times D_1) \times \sin\left(-\omega \times D_1 + \frac{3\pi}{2}\right)$$
$$y = (r_1 + 0.00565 \times D_1) \times \cos\left(-\omega \times D_1 + \frac{3\pi}{2}\right) \quad (13)$$

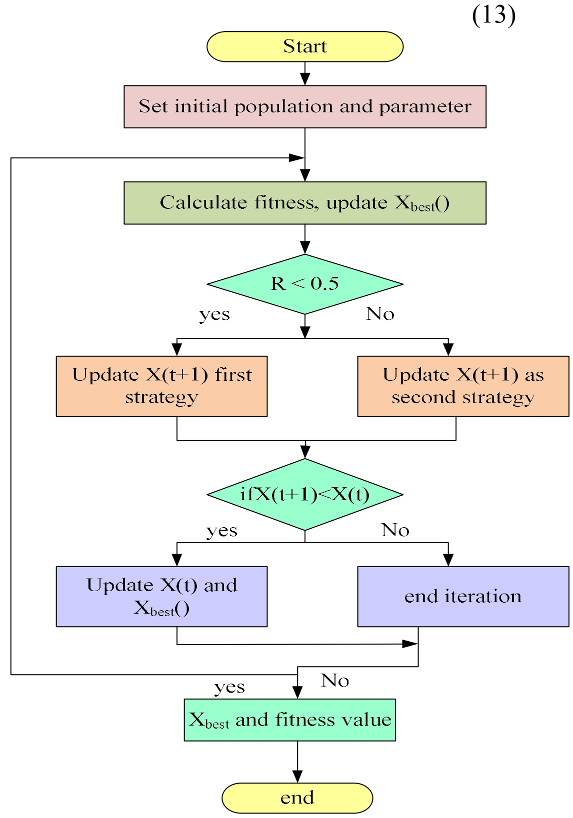

Figure 6: Structure of AOA

Here, the search cycles number is r1, a random integer D1 from 1 to D dimension and a constant of 0.005 is ω.

In third strategy, Aquila finds prey location then it will fall vertically for introductory preying. In this

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strategy speed be reduced and behaviour is expressed in equation (14),

$$X(t+1)=\alpha\times(X_M(t)-X_{best}(t))-rand+(rand(LB-UB)+LB)\times\delta \quad (14)$$

Here, the adjustment factors are , the search space lower and upper bounds of is represented as LB and UB.

In fourth strategy Aquila goes to the land and catches the prey and the behaviour is expressed in equation (15). The quality function is expressed in equation (16),

$$X(t+1)=X_{best}(t)\times QF-(X(t)\times G_1\times rand)-LF(D)\times G_2+G_1\times ran \quad (15)$$

$$QF(t)=t^{\frac{2\times rand-1}{(1-T)^2}} \quad (16)$$

$$G_1=rand\times 2-1$$

$$G_2=\left(1-\frac{t}{T}\right)\times 2 \quad (17)$$

Here, QF is the quality function of the average search strategy, random motion parameter is represented as G1 which lies between -1 and 1. Flight slope is represented as G2 which decreases from 2 to 0. G1 and G2 are expressed in equation (17).

4. RESULTS AND DISCUSSION

Early prediction of heart diseases is essential task to save human life because deaths are increased day by day with late prediction of heart diseases. Thus, many researches are involved to make research in this field. The proposed work is analyzed with the input data of Electrocardiogram (ECG) from patient and these data are tend to pre-process for removing the noise with the help of filters. The data is then classified using CNN and neural network is trained using proposed dataset. The CNN performance is improved by using the AOA optimization algorithm to select weight parameters. The proposed system's performance is evaluated by comparing the proposed CNN with other existing CNN models of recall, sensitivity, accuracy, specificity, precision, F-Measure, NPV, FPR, FNR, MCC, FRR, and FDR using the physionet dataset. These are thoroughly explained as follows:

5.1 Training with physionet Dataset:

This dataset is given to the proposed system to train the model with clinical data, which consists of 21837 clinical 12-lead ECG records captured every 10 seconds from 18885 patients. The patients are a mix of male and female, with 52% male and 48% female patients ranging in age from 0 to 95 years [37]. The records and the disease affected at each record are illustrated in table 2.

Table 2: Different types of diseases at each record

Records	Super class	Description
5486	MI	Myocardial Infarction
5250	STTC	ST/T Change
4907	CD	Conduction Disturbance
2655	HYP	Hypertrophy
9528	NORM	Normal ECG

This dataset is given to the proposed system to train the neural network which is analyzed with the test data after that the predicted output is obtained.

5.2. Evaluation matrix and discussion of result

The proposed system performance is evaluated using parameters such as precision, accuracy, F-Measure, recall, specificity, sensitivity, NPV, FPR, FNR, MCC, FRR, and FDR.

Table 3: Analysis of proposed system TN, TP, FP, FN values with existing technologies

Algorithms	TP	TN	FP	FN
Proposed AOA_CNN	402.4	1669	19.8	19.8
CNN	393.6	1660.2	28.6	28.6

RNN	382.4	1649	39.8	39.8
LSTM	376.4	1643	45.8	45.8

These values are based on the classifier's prediction of trained and test data. False Positive (FP), False Negative (FN), True Negative (TN), True Positive (TP) and the predicted values (TN). Table 3 shows these values for proposed and existing technologies.

In the above table the proposed system has the high positive prediction and the other existing methods has less positive prediction but the negative prediction is low in proposed work. Thus the proposed work delivered accurate output than the other existing technologies.

5.2.1. Comparison analysis of proposed system with other existing technologies

The proposed technology's performance is evaluated by comparing it to other existing technologies using various performance matrices.

Accuracy is used to find the best model in a dataset by combining input and trained data.

Precision parameter finds the positive predictions in the whole predicted positive values which mean the quality of positive prediction is observed.

Recall observes the total quality of the true positive outcomes of the prediction which describes that the total accurate prediction is found.

F-Measure analyzes the mean value of the prediction and recall.

Sensitivity identifies the positive instances in the prediction, by using this performance of the model is evaluated.

Specificity shows the negative instances from the prediction.

FPR defines the incorrect positive results among all thee negative results while testing the system.

FNR define the ratio of false positive results and total positive results.

MCC is the statistical rate that obtain high result when the prediction achieve good results in all test.

FRR is the ratio of positive results below the threshold value.

FDR is a measure of accuracy when multiple hypotheses are being tested at once.

The values of these parameters are illustrated in tables 4, 5, 6 and 7 and the tested accuracy value of existing works is illustrated in table 8.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP}$$

$$\Pr ecision = \frac{TP}{FP + TP}$$

$$\mathrm{Re}\,call = \frac{TP}{FN + TP}$$

Table.4: Precision, Recall and Accuracy values of proposed and existing methods

Algorithm	Accuracy	Precision	Recall
Proposed AOA_CNN	0.981241118	0.953102795	0.953102795
CNN	0.972903837	0.932259593	0.932259593
RNN	0.962292752	0.905731881	0.905731881
LSTM	0.956608243	0.891520606	0.891520606

Figure 7 shows the contrast of proposed method with existing technology of recall, precision and accuracy in which accuracy of proposed and existing methods is 0.981241118, 0.972903837, 0.962292752and 0.956608243 respectively. Thus the accuracy is high in proposed method than other existing methods.

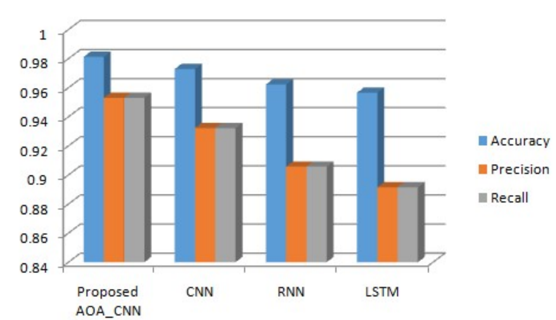

Figure 7: Comparative performance of accuracy, precision and recall

The precision of proposed and existing methods is 0.953102795, 0.932259593, 0.905731881 and 0.891520606 respectively. Thus the precision is high in proposed method than other existing methods and the recall of proposed and existing methods is 0.953102795, 0.932259593, 0.905731881 and 0.891520606 respectively. Thus the recall is high in proposed method than other existing methods.

$$Sensitivity = \frac{TP}{FN + TP}$$

$$Specificity = \frac{TN}{FP + TN}$$

$$F - Measure = \frac{2 \times recall \times precision}{recall + precision}$$

Table 5: F- Measure, specificity and sensitivity values of proposed and existing methods

Algorithm	Sensitivity	Specificity	F-Measure
Proposed AOA_CNN	0.953102795	0.988275699	0.953102795
CNN	0.932259593	0.983064898	0.932259593
RNN	0.905731881	0.97643297	0.905731881
LSTM	0.891520606	0.972880152	0.891520606

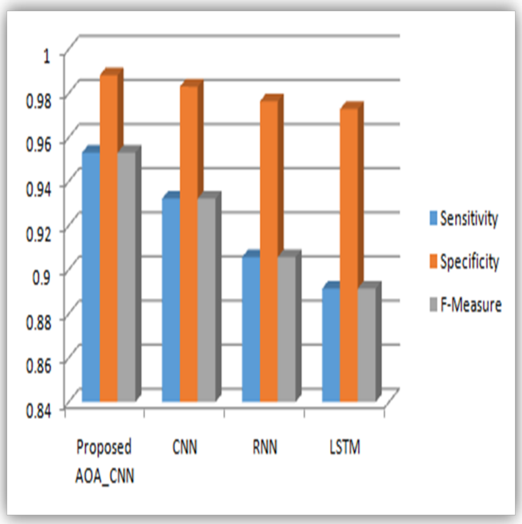

Figure 8: Comparison of performance in terms of F-Measure, specificity and sensitivity

Figure 8 compares the sensitivity of the proposed method to that of existing technology in terms of sensitivity, specificity and F-Measure is 0.953102795, 0.932259593, 0.905731881 and 0.891520606. Thus sensitivity is high in proposed method than other existing methods.

The specificity of proposed and existing methods is 0.988275699, 0.983064898, 0.97643297 and 0.972880152 respectively. The F-Measure of proposed and existing methods is 0.953102795, 0.932259593, 0.905731881 and 0.891520606 respectively. Thus the F-Measure is high in proposed method than other existing methods.

$$FPR = \frac{FP}{FP + TN}$$

$$FNR = \frac{FN}{FN + TP}$$

Table 6: FNR, FPR and NPV and values of proposed and existing methods

Algorithm	NPV	FPR	FNR
Proposed AOA_CNN	0.988275699	0.011724301	0.046897205
CNN	0.983064898	0.016935102	0.067740407
RNN	0.97643297	0.02356703	0.094268119
LSTM	0.972880152	0.027119848	0.108479394

Figure 9 shows the contrast of proposed method with existing technology in terms of FPR, NPV and FNR in which NPV is 0.988275699, 0.983064898, 0.97643297 and 0.972880152 respectively. Thus the NPV is high in proposed method than other existing methods.

The FPR of existing and proposed methods is 0.011724301, 0.016935102, 0.02356703 and 0.027119848 respectively. The FNR of existing and proposed methods is 0.046897205, 0.067740407, 0.094268119 and 0.108479394 respectively. Thus the FPR and FNR rates are low in proposed method than other existing methods which concludes that the proposed method has low false predictions.

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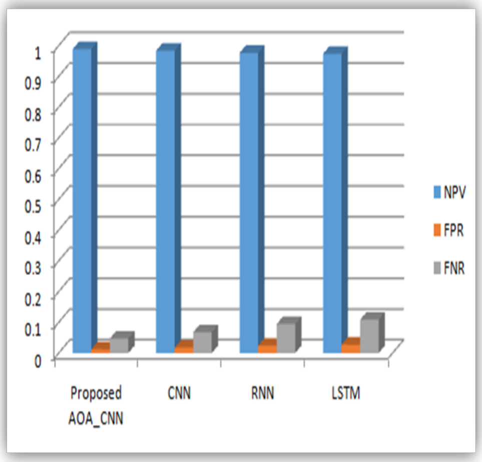

Figure 9: Performance comparison in terms of NPV, FPR and FNR

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(FP+TP)(FN+TP)(FP+TN)(FN+TN)}}$$

$$FRR = \frac{FP}{FN + FP}$$

$$FDR = \frac{FP}{FP + TP}$$

Table 7: MCC, FRR and FDR values of proposed and existing methods

Algorithm	MCC	FRR	FDR
Proposed AOA_CNN	0.941378494	0.046897205	0.046897205
CNN	0.915324491	0.067740407	0.067740407
RNN	0.882164851	0.094268119	0.094268119
LSTM	0.864400758	0.108479394	0.108479394

Figure 10 shows the contrast of proposed method with existing technology in terms of MCC, FRR and FDR in which the MCC of proposed and existing methods is 0.941378494, 0.915324491, 0.882164851 and 0.864400758 respectively. Thus the MCC is high in proposed method than other existing methods.

The FRR of proposed and existing methods is 0.046897205, 0.067740407, 0.094268119 and 0.108479394 respectively. The FDR of proposed and existing methods is 0.046897205, 0.067740407, 0.094268119 and 0.108479394 respectively. Thus the FRR and FDR rates are low in proposed method than other existing methods which concludes that the proposed method has low false predictions.

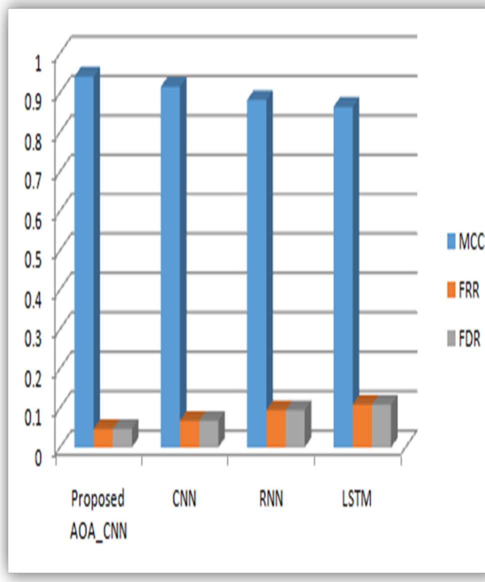

Figure 10: Performance comparison in terms of MCC, FRR and FDR

Table 8: Performance evaluation of proposed work in comparison to existing work

Authors	Accuracy
Proposed	98%
Tulasi Krishna Sajja *et al* [30]	94%
Awais Mehmood *et al* [31]	97%
Peyman Rezaei Hachesu *et al* [32]	83.5%
Alizadeh-dizaj *et al* [33]	95.5%

Table 8 shows the proposed work has high performance than the other existing works where accuracy parameter is observed for calculation. Thus the proposed work has 98% high accuracy.

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6. CONCLUSION

A DCNN was used to detect the heart which is the combination of CNN and AOA. In the DCNN, the hyper parameters were optimized with the help of AOA algorithm. CNN works well on images. ECG images are used for predicting of heart disease. The idea behind this research was to combine ECG images as well as clinical data in order to give high performance in prediction. ECG images were pre-processed to scale down the size and then CNN is applied and prediction is done. In this case, different methods for pre processing are applied and best pre-processing method is found in this work. ECG images are taken and different mathematical methods like Fourier transform, DCT or combination of Fourier transform and DCT etc are applied and best method is found. The proposed model is then implemented in MATLAB and performance is evaluated by comparing the proposed CNN with other existing CNN model in terms their performance matrices using physionet dataset.

REFERENCES:

[1] L.J.Burchill, M.G.Y.Lee, V.P.Nguyen and K.K.Stout, "Heart Failure in Adult Congenital Heart Disease", An International Journal of Cardiology Clinics, Vol.38, No.3, 2020, pp.457-469.

[2] R.Sonawane and H.Patil, "Automated heart disease prediction model by hybrid heuristic-based feature optimization and enhanced clustering", An International Journal of Biomedical Signal Processing and Control, Vol.72, No.103260, 2022.

[3] M.S.Pathan, A.Nag, M.M.Pathan and S.Dev, "Analyzing the impact of feature selection on the accuracy of heart disease prediction", An International Journal of Healthcare Analytics, Vol.2, No.100060, 2022.

[4] J.Rodriguez, S.Prieto and L.J.R.Lopez, "A novel heart rate attractor for the prediction of cardiovascular disease", An International Journal of Informatics in Medicine Unlocked, Vol.15, No.100174, 2019.

[5] A.Kodra, T.Rambhatla, N.Sharma, C.Basman, E.Depasquale and N.Coplan, "Non Invasive Imaging (Echocardiography, Nuclear, PET, MR and CT) inferior Q wave and underlying ischemic heart disease prediction study", An International Journal of the American College of Cardiology, Vol.73, No.9, 2019, pp.1565.

[6] J.J.Beunza, E.Puertas, E.G.Ovejero, G.Villalba, E.Condes, G.Koleva, C.Hurtado and M.F.Landecho, "Comparison of machine learning algorithms for clinical event prediction (risk of coronary heart disease)", An International Journal of Biomedical Informatics, Vol.97, No.103257, 2019.

[7] M.Ali, B.K.Paul, K.Ahmed, F.M.Bui, J.M.W.Quinn and M.A.Moni, "Heart disease prediction using supervised machine learning algorithms: Performance analysis and comparison", An International Journal of Computers in Biology and Medicine, Vol.136, No.104672, 2021.

[8] R.Valarmathi and T.Sheela, "Heart disease prediction using hyper parameter optimization (HPO) tuning", An International Journal of Biomedical Signal Processing and Control, Vol.70, No.103033, 2021.

[9] F.Ali, S.E.Sappagh, S.M.Riazul Islam, D.Kwak, A.Ali, M.Imran and K.SupKwakh, "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion", An International Journal of Information Fusion, Vol.63,2020, pp.208-222.

[10] E. D. Übeyli.,"Combining recurrent neural networks with eigenvector methods for classification of ECG beats", Digital Signal Processing, Vol 19, 2009, pp. 320–329.

[11] R. R. Sharma, M. Kumar, R. B. Pachori., "Automated CAD identification system using time frequency representation based on eigenvalue decomposition of ECG signals" Machine Intelligence and Signal Analysis, 2019, pp. 597–608.

[12] U. Stern, R. He,Yang,"Analyzing animal behavior via classifying each video frame using convolutional neural networks", Scientific Reports, Vol 5, 2015, pp. 14351.

[13] Kiranyaz, T. Ince, M. Gabbouj,"Real-time patient-specific ECG classification by 1-D convolutional neural networks", IEEE Transactions on Biomedical Engineering,Vol 63, 2016, pp.664–675.

[14] A.Sharma, T.Pal and V.Jaiswal, "Chapter 12 - Heart disease prediction using convolutional neural network", An International Journal of Cardiovascular and Coronary Artery Imaging, Vol.1, 2022, pp.245-272.

[15] M.H.Vafaie, M.Ataei and H.R.Koofigar, "Heart diseases prediction based on ECG signals' classification using a genetic-fuzzy system and

dynamical model of ECG signals", An International Journal of Biomedical Signal Processing and Control, Vol.14, 2014, pp.291-296.

[16] A.Rath, D.Mishra, G.Panda, S.C.Satapathy and K.Xia, "Improved heart disease detection from ECG signal using deep learning based ensemble model", An International Journal of Sustainable Computing: Informatics and Systems, Vol. 35, No. 100732, 2022.

[17] A.S.Eltrass, M.B.Tayel and A.I.Ammar, "A new automated CNN deep learning approach for identification of ECG congestive heart failure and arrhythmia using constant-Q non-stationary Gabor transform", An International Journal of Biomedical Signal Processing and Control, Vol.65, No.102326, 2021.

[18] M.F.Aslan, K.Sabanci and A.Durdu, "A CNN-based novel solution for determining the survival status of heart failure patients with clinical record data: numeric to image", An International Journal of Biomedical Signal Processing and Control, Vol.68, No.102716, 2021.

[19] A.A.Samir, A.R.Rashwan, K.M.Sallam, R.K.Chakrabortty, M.J.Ryan and A.A.Abohany, "Evolutionary algorithm-based convolutional neural network for predicting heart diseases", An International Journal of Computers and Industrial Engineering, Vol.161, No.107651, 2021.

[20] R.F.Pinto, C.D.B.Borges, A.M.A.Almeida and I.C.Paula, "Static Hand Gesture Recognition Based on Convolutional Neural Networks", An International Journal of Electrical and Computer Engineering, 2019.

[21] G.Kaur, R.Sinha, P.K.Tiwari, S.K.Yadav, P.Pandey, R.Raj, A.Vashisth and M.Rakhra, "Face mask recognition system using CNN model", An International Journal of Neuroscience Informatics, Vol.2, No.3, 2022.

[22] B.Rostami, D.M.Anisuzzaman, C.Wang, S.Gopalakrishnan, J.Niezgoda and Z.Yu, "Multiclass wound image classification using an ensemble deep CNN-based classifier", An International Journal of Computers in Biology and Medicine, Vol.134, No.104536, 2021.

[23] R.Mostafiz, M.S.Uddin, Nur-A-Alam, M.Reza and M.M.Rahman, "Covid-19 detection in chest X-ray through random forest classifier using a hybridization of deep CNN and DWT optimized features", An International Journal of King Saud University Computer and Information Sciences, 2020.

[24] I.S.Polonskaia, I.R.Aliev and N.O.Nikitin, "Automated Evolutionary Design of CNN Classifiers for Object Recognition on Satellite Images", Procedia Computer Science, Vol.193, 2021, pp.210-219.

[25] S.Irin Sherly, G.Mathivanan, "ECG Signal Noises Versus Filters for Signal Quality Improvement", 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies, 2021, 9392621.

[26] S.Ahlawat and A.Choudhary, "Hybrid CNN-SVM Classifier for Handwritten Digit Recognition", Procedia Computer Science, Vol.167, 2020, pp 2554-2560.

[27] S.Irin Sherly, G.Mathivanan, "An Ensemble based Heart Disease Prediction using Gradient Boosting Decision Tree", Turkish Journal of Computer and Mathematics Education, Vol.12, No. 10, 2021, pp.3648-3660.

[28] C.Zhang, X.Pan, H.Li, A.Gardiner, I.Sargent, J.Hare and P.M.Atkinsona, "A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification", ISPRS Journal of Photogrammetry and Remote Sensing, Vol.140, 2018, pp.133-144.

[29] S.Irin Sherly, G.Mathivanan, "An efficient honey badger based Faster region CNN for chronic heart Failure prediction", Biomedical Signal Processing and Control, Vol 79, No. 104165, 2023.

[30] W.Li, M.Zuo, H.Zhao, Q.Xu and D.Chen, "Prediction of coronary heart disease based on combined reinforcement multitask progressive time-series networks", An International Journal of Methods, Vol.198, 2022, pp.96-106.

[31] L.Ma and L.Liang, "A regularization method to improve adversarial robustness of neural networks for ECG signal classification", An International Journal of Computers in Biology and Medicine, Vol.144, No.105345, 2022.

[32] R.Abacherli, F.Odille, C.Pasquier and S.J.Jakob, "Suppression of MR gradient artefacts on electrophysiological signals based on an adaptive real-time filter with LMS coefficient updates", An International Journal of MAGMA Magnetic Resonance Materials in Physics Biology and Medicine, Vol.18, 2005, pp.41–50.

[33] R.Kher, "Signal Processing Techniques for Removing Noise from ECG Signals", An International Journal of Biomedical Engineering and Research, Vol.3, No.101, 2019, pp.1-9.

[34] S.Bai, W.Gu and L.Kong, "Interweave features of Deep Convolutional Neural Networks for semantic segmentation", An International Journal of Engineering Applications of Artificial Intelligence, Vol.109, No.104587, 2022.

[35] L.Abualigah, D.Yousri, M.A.Elaziz, A.A.Ewees, M.A.A.Al-qaness and A.H.Gandomi, "Aquila Optimizer: A novel meta-heuristic optimization algorithm", An International Journal of Computers and Industrial Engineering, Vol.157, No.107250, 2021.

[36] W.Ye, X.Ding, N.Putnam, R.Farej, R.Singh, D.Wang, S.Kuo, S.X.Kong, J.C.Elliott, J.Lott and W.H.Herman, "Development of clinical prediction models for renal and cardiovascular outcomes and mortality in patients with type 2 diabetes and chronic kidney disease using time-varying predictors", An International Journal of Diabetes and its Complications, Vol.36, No.5, 2022.

[37] T.K.Sajja and H.K.Kalluri, "A Deep Learning Method for Prediction of Cardiovascular Disease Using Convolutional Neural Network", RIA, Vol.34, No.5, 2020, pp.601-606.

[38] A.Mehmood, M.Iqbal, Z.Mehmood, A.Irtaza, M.Nawaz, T.Nazir and M.Masood, "Prediction of Heart Disease Using Deep Convolutional Neural Networks", Arabian Journal for Science and Engineering, 2020.

[39] P.R.Hachesu, M.Ahmadi, S.Alizadeh and F.Sadoughi, "Use of Data Mining Techniques to Determine and Predict Length of Stay of Cardiac Patients", 2013, pp.121-129.

[40] A.dizaj and G.Risk, "Prediction and Stratification of Patients with Stroke Using Data Mining Techniques", School of Management and Medical Informatics, 2018.