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Enhanced Deep learning assisted Convolutional Neural Network for Heart Disease Prediction on the internet of medical things platform

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ABSTRACT The diagnosis of heart disease has become a difficult medical task in the present medical research. This diagnosis depends on the detailed and precise analysis of the patient’s clinical test data on an individual’s health history. The enormous developments in the field of deep learning seek to create intelligent automated systems that help doctors both to predict and to determine the disease with the internet of things (IoT) assistance. Therefore, the Enhanced Deep learning assisted Convolutional Neural Network (EDCNN) has been proposed to assist and improve patient prognostics of heart disease. The EDCNN model is focused on a deeper architecture which covers multi-layer perceptron’s model with regularization learning approaches.

Furthermore, the system performance is validated with full features and minimized features. Hence, the reduction in the features affects the efficiency of classifiers in terms of processing time, and accuracy has been mathematically analyzed with test results. The EDCNN system has been implemented on the Internet of Medical Things Platform (IoMT) for decision support systems which helps doctors to effectively diagnose heart patient’s information in cloud platforms anywhere in the world. The test results show compared to conventional approaches such as Artificial Neural Network (ANN), Deep Neural Network (DNN), Ensemble Deep Learning-based smart healthcare system (EDL-SHS), Recurrent neural network (RNN), Neural network ensemble method (NNE), based on the analysis the designed diagnostic system can efficiently determine the risk level of heart disease effectively. Test results show that a flexible design and subsequent tuning of EDCNN hyperparameters can achieve a precision of up to 99.1 %.

INDEX TERMS Heart Disease Prediction, Convolutional Neural Network, Deep Learning.

I. Introduction

In today’s world, heart disease is the leading impact of death to all the age groups. Hence, the health sector necessities to improve the need to predict heart attacks [1] using various deep learning techniques. Precise and accurate diagnosis of heart disease depends primarily on prior knowledge and information from related pathological events [2]. Hence, Heart disease patients body parameters such as blood pressure, cigarette smoking, cholesterol, diabetes, and sex [3,4] need to monitor in all the aspect [5]. These variables are independent and find a good choice for artificial intelligence (AI) and machine learning systems.

Further, The Prediction of the disease using machine learning techniques is the main topic [6], which has been addressed in this research. The deep learning has been widely used for days, which shows a noticeable improvement in prediction and analysis of heart disease [7]. Prediction is an area in which this deep learning has been utilized [8,9] and

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shows prominent outcomes in various medical fields. Hence in this paper, the prediction of heart disease by processing patient data to calculate the chance of heart ailment has been mathematically computed with distributive functions.

In General, [10], Cardiovascular disease is a term for many types, including rheumatic, coronary, and congenital heart disease. Hence, Heart activity has been analyzed during exercise, resting, and working [11, 12]. Coronary artery illness signs include chest pain, discomfort, respiratory shortness, sweatiness, heart palpitation, dizziness, and fatigue. Research has recently made significant progress in these fields, especially given the amount and complexity of data involved, deep learning, and classification technologies [13] to predict heart disease effectively [14]. Current methods for diagnosing the severity of heart disease in patients include stress testing, chest x-ray, coronary angiogram, cardiac magnet resonance imaging (MRI) [15], and electrocardiogram (EKG)[16], etc..,. Medical science and data mining techniques are used to diagnose different signal types of metabolic syndromes during physical activities such as exercise, resting, and working [17]. Classification data mining is the sign of a role for prediction and data research in the extrapolation of heart disease [18-20].

Shahid Mehmood Awan et al. [21] reported that the Artificial Neural Network (ANN) for the prediction of Heart disease uses bioinformatics applications to extract patterns from datasets by various data mining techniques. The extraction of attributes is very successful in prediction mining knowledge. Different trends to predict the heart condition can be extracted using an ANN, which depends on human anatomy. A short "Neural networks" (NN) and a multi-level Perceptron concept help to analyze the human brain's single neuron. It has several views on several levels, and the perception has an impact on value, and output has been shown in Figure 1. Here the hidden layer with a predetermined value and the last output layer with tests has been reported.

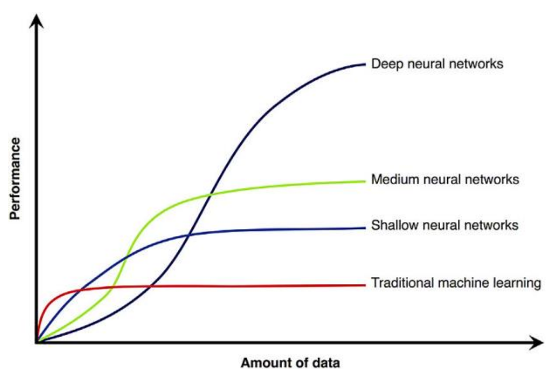

FIGURE. 1. **Survey on Various neural network and its importance [22]**

Nathalie-Soa Tomov et al. [23] introduced the Deep Neural Network (DNN) for detecting heart disease, and the results have discovered in the process of the five-level DNN architecture for Algorithmic Risk-reduction and Optimization for the best prediction accuracy as shown in Figure.2. The architecture reported by the authors driven by optimization and handles missing data and data outliers automatically with high performance. To evaluate the optimized architectures, the k cross-validation has been utilized, and the Matthews correlation coefficient (MCC) has been analyzed. The survey is carried out on the publicly available data set of Cleveland's medical information and the open-source developments to make the use of DNNs in the medicine sector.

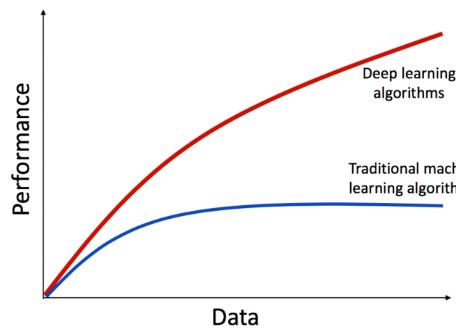

FIGURE.2. **Survey on Various Deep learning assistance with traditional algorithms [24]**

Shreshth Tuli et al. [25] initialized an Ensemble Deep Learning-based smart healthcare system (EDL-SHS) for automatic heart disease diagnosis in an intergraded IoT based Fog computing environment. Health Fog provides healthcare as a fog service with IoT equipment and handles the data of cardiac patients as requested by users effectively. Here, the Fog-enabled Cloud Framework, Fog-Bus, uses the latency, bandwidth, power consumption, jitter, precision, and performed time to implement and evaluate a proposal model's performance. Health-Fog can be programmed to give the best quality of service or forecast accuracy for various fog computing scenarios and different user needs. Deep learning methods with high precision needs high computer resources for training and prediction. This works to integrate complex deep learning networks into the edge computing paradigms by utilizing new communication techniques and models such as assembly, that permit a high level of accuracy with low latencies.

Edward Choi et al. [26] introduced the Recurrent neural network (RNN) for early detection of heart failure. Further, the new neural network model models (RNNs) have adapted for detecting twenty to 18-month observation window cases and controls timely events (for instance, disease diagnosis, medication instructions procedural orders, etc.). Model efficiency metrics have been contrasted with the regularized regression of logistics, where the neural network and vector support systems approach to the K-nearest classifier for analysis. Deep learning models designed to exploit time relationships appear in the short 12 to 18-month observer window to improve the performance of models to predict incident heart failure.

Resul Das et al. [27] proposed the Neural network ensemble method (NNE) for the effective diagnosis of heart disease. The ensemble-based approaches create new models by integrating the retrograde probabilities of several models. This can create more effective models with the method to carry out the test experiments. Cardiac disease dataset was tested to diagnose heart disease. The ensemble model was developed using three separate models of the neural network, and It allows the user to deal with various methods of performance assessment. It enables the user to from multiple points of view to assess their system performance.

Outcomes of the research

To overcome these issues, in this paper, an Enhanced deep convolutional neural network (EDCNN) has been proposed for the early detection of heart disease and diagnosis. The use of the data analysis techniques for deep learning (DL) will ease the need for expertise and the probability of human error, thus increasing prediction accuracy. Hence, EDCNN shows promising results in the design and tuning of architectures for the detection of heart disease with increased scope based on routine clinical data. Test results show that a flexible design and subsequent tuning of EDCNN hyperparameters can achieve a precision of up to 99 %.

This research has been developed EDCNN approach to detect heart disorders in patients and to improve diagnostic precision using deep learning-based prediction models, and classification the classification and diagnostic models developed for this study include two phases:

Phase:1- Designed deep learning algorithms are focused on a deep multi-layer interpretation of system and design regulation. Further, the diagnosis pattern is used to detect if patients have heart disease based on the training model.

Phase:2- The performance has been validated for precision, the error probability, specificity, sensitivity, accuracy, and Region of Convergence ROC curve [19]. Further, a remote patient monitoring (RPM) platform is proposed, that is skillful enough to screen the patient typically with IoMT [20] assistance to collect information about the patients' health parameters such as pulse, ECG and blood pressure and send a crisis warning to the caretaker with his or her actual condition and complete remedial details. Based on the discussion the scope of the paper is listed as follows,

The scope of this research is stated as follows,

To determine the accuracy in recognition of heart disease using an enhanced deep learning assisted convolutional neural network approach has been proposed.

Bayesian classification systems have been developed to analyze the minimum error rate, and the multi-layered perceptron algorithm is composed of artificial neurons, including hidden layers for the problems of binary classification

The experimental results have been performed using the UCI repository dataset (https://archive.ics.uci.edu/ml/datasets/Heart+Disease), and the proposed system has high performance in terms of precision and accuracy of detecting heart disease.

Various sections of the paper are listed as follows:

Section 1: discussed the introduction and existing methods of heart disease prediction methods.

In section 2: The Enhanced Deep learning assisted Convolutional Neural Network (EDCNN) has been proposed to assist and improve patient accuracy and reliability in diagnosis and prognostics of heart disease.

In section 3: The experimental result has been illustrated.

Finally, Section 4 concludes the research paper with future scope.

II. ENHANCED DEEP CONVOLUTIONAL NEURAL NETWORK (EDCNN):

In this paper, EDCNN has been proposed for the early prediction of heart disease and diagnosis. The UCI repository dataset has been utilized for the diagnosis purpose, and CNN classifier and multi-layer perceptron (MLP) module has been used to classify basic ECG heartbeats for feature extraction. The CNN functions as a feature extractor block due to the beat classification problem. The final activations obtaining from the last convolution layer are used as inputs in a network. A batch normalization layer and an activation function follow the basic convolutional layer using a mathematical convolutional process. As shown in the string of 1, hyperparameters are used to perform a conveyor operation in each layer using 20 one-dimensional filters (i.e., kernels) {10, 15, and 20}. The convolutional block can thus be formalized as a series of Three operations, defined by the equations below— evolution, batch normalization, and non-linear activation:

Preposition 1: Longitudinal analysis and process architecture

$$z=S*y+a \quad (1)$$

$$bn=BN(z) \quad (2)$$

$$act=ReLU(bn) \quad (3)$$

As shown in the above equation where * is the convolutional operator, S is the convolutional layer variable, y denotes the input time series, a is the bias, where BN is the Batch Normalization function and ReLU as the activation function. A soft-max function is used in the final label for longitudinal data analysis, which has been shown in Figure.4. Recent research has shown that pooling operations do not impact on the classification and may affect overfitting the convolution blocks.

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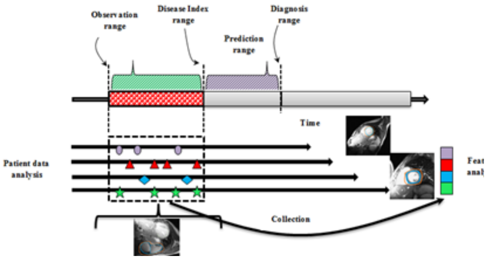

Figure.3. longitudinal data analysis for patient

The score gradients for class b as a global average pooling for the last function maps are determined for the weight used in a linear combination of forwarding activation maps the feature vector, which helps to analyze several windows such as prediction, diagnosis, and observation as shown in Figure.3. In particular, the method involves calculating the gradient of class b (z^b) score concerning the C that is global-average-pooled to get the weights β_l^b .The weights are determined accordingly that helps to analyze the risk of the disease: Therefore:

$$\beta_l^b = \frac{1}{n}\sum_j \sum_i \frac{\partial z^b}{\partial C_{ji}^l} \tag{4}$$

As shown in equation (4) where β_l^b captures the significance of feature map l for a target class b. The map function for class b is determined as a weighted combination of the feature map, as following by ReLU.

$$map = ReLU\left(\sum_l \beta_l^b C^l\right) \tag{5}$$

This technique has been used in the derivative of class activation map b, indicating the value of

The activation at temporal location y_j; results in an input time series being classified as a class before the efficient representation of data and deep learning classification, preprocessing of data is essential and should be trained and tested adequately. The dataset has been preprocessed for efficient use by the classifier techniques such as delete of missing values, regular scalar, or MinMax Scalar. Figure 4. shows the architecture of the proposed EDCNN system. Here the Feature selection is needed for deep learning assistance because sometimes non-relevant features affect the deep learning classification efficiency. The selection of features increases the precision of classification and reduces the model time. The DL algorithms have been used for selecting features, and a multi-layer perceptron algorithm has been utilized for binary classification problems.

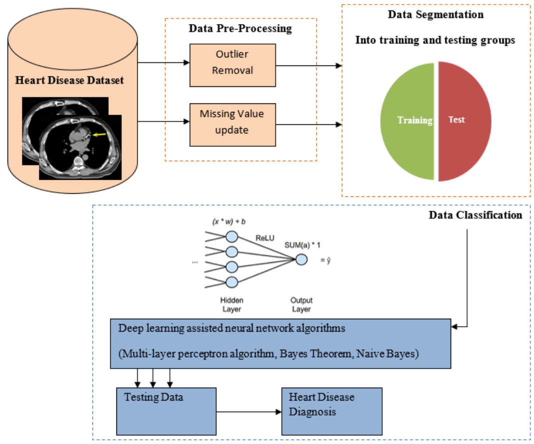

Figure.4: The proposed EDCNN method architecture

Preposition 2: Bayes Net and Multi-Layer Perceptron

The Bayesian network is a probability theory based graphical prediction model. Bayesian networks are focused on probabilistic distributions and use probability laws to forecast and diagnose heart disease. All discrete and continuous variables are provided by Bayesian networks, as shown in Figure.5.

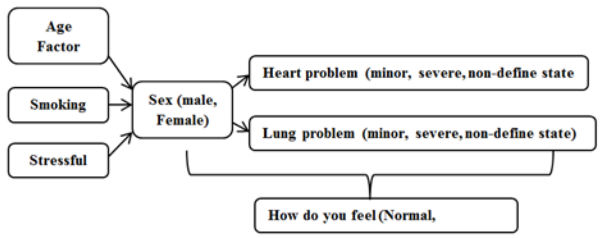

Figure.5. Bayesian networks for prediction analysis

The network is represented as a group of variables with acyclic directed graphs describing the conditional dependencies. The edges between nodes in the Bayesian network represent dependent features, while the not linked nodes are independent conditionally.

Let's consider Y be the evidence that is dependent on m attributes $Y = \{C_1, C_2, \ldots . C_m\}$. Let G is a hypothesis that the evidence belongs to a class B. The likelihood of hypothesis G, given the evidence Y, is depicted as $Q(G|Y)$. $Q(Y|G)$ is the posterior likelihood of Y condition on G. The posterior probability can be estimated utilizing the Bayes theorem,

$$Q(G|Y) = Q(Y|G)Q(G)/Q(Y) \tag{6}$$

As shown in equation (6), where Q(G) is the likelihood of the hypothesis being actual, Q(G) is the likelihood of the evidence. $Q(Y|G)$ is the likelihood of the evidence given that the hypothesis is correct and $Q(Y|G)$ is the likelihood of the hypothesis given that the evidence represents.

The classification or only the Bayesian classification of Naïve Bayes is based on the theorem Bayes. This is a particular case of the Bayesian network and a classifier based

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on probability-based on age, sex, and various problems, as mentioned in Figure.6. All functions are conditionally autonomous in the Naïve Bayes network. Consequently, the modifications to one feature do not affect another. The algorithm of Naïve Bayes is suitable for classified data sets of high dimensions. The algorithm of the classifier is independent of the condition. Being independent means that the value of the attribute is distinct from the importance of the other characteristics of a class.

Let's consider D is a set of training data and linked class labels. Every tuple in the dataset is stated with m attributes that are depicted by $Y = \{C_1, C_2, \ldots. C_m\}$. Let there be n classes denoted by $B_1, B_2, \ldots B_n$. For the given tuple Y, classifier forecast that Y belongs to the class having the highest posterior likelihood conditioned on Y. The Naive Bayes classifier forecast that the tuple Y belongs to the class B_j,

$$Q(B_j|Y) > Q(B_i|Y) for 1 \leq i \leq n, i \neq j \tag{7}$$

Therefore, $Q(B_i|Y)$ is maximized. The class B_j for which $Q(B_i|Y)$ is maximized is called the maximum posterior hypothesis. According to the Bayes theorem,

$$Q(B_j|Y) = \frac{Q(Y|B_j)Q(B_j)}{Q(Y)} \tag{8}$$

if the values of the attributes are conditionally independent of one another.

$$Q(Y|B_j) = \prod_{l=1}^{m} Q(y_l|B_j) \tag{9}$$

As shown in equation (9) where y_l denotes to the value of the attribute C_l for tuple Y.

if C_l is categorical, then $Q(y_l|B_j)$ is the number of tuples of class B_j in D having the y_l for C_l divided by $|B_{j,D}|$, the number of tuples of class B_j in D. The classifier forecast the class label of Y is the class B_j,

$$Q(Y|B_j)Q(B_j) > Q(Y|B_i)Q(B_i) \;\; for\ 1 \leq i \leq n, \;\; i \neq j \tag{10}$$

Bayesian classification systems are useful in that they are classified at the minimum error rate, as shown in the Algorithm1.

Algorithm 1: Multi-layer Perceptron Algorithm

Initialize weights and biases in M, where M is the Network

While the condition is true {

For every training tuple Y in D {

For every input layer unit, i {

$\boldsymbol{O_i = J_i}$

For every hidden or output layer unit i {

$\boldsymbol{J_i = \sum_j S_{ji} O_j + \theta_i}$

$\boldsymbol{O_i = \frac{1}{1+e^{-J_i}}}$

For every unit i in the output layer

$\boldsymbol{Err_i = O_i(1 - O_i)(R_i - O_i)}$

For every unit i in the hidden layer, from the last to the first hidden layer

$\boldsymbol{Err_i = O_i(1 - O_i) \sum_l Err_l s_{il}}$

For every weight $\boldsymbol{s_{ji}}$ in M {

$\Delta \boldsymbol{s_{ji}} = (\boldsymbol{l})\boldsymbol{Err_j O_j}$

$\boldsymbol{s_{ji}} = \boldsymbol{s_{ji}} + \Delta \boldsymbol{s_{ji}}\}$

For every bias $\boldsymbol{\theta_i}$ in M {

$\Delta \boldsymbol{\theta_i} = (\boldsymbol{k})\boldsymbol{Err_i}$

$\boldsymbol{\theta_i} = \boldsymbol{\theta_i} + \Delta \boldsymbol{\theta_i}$

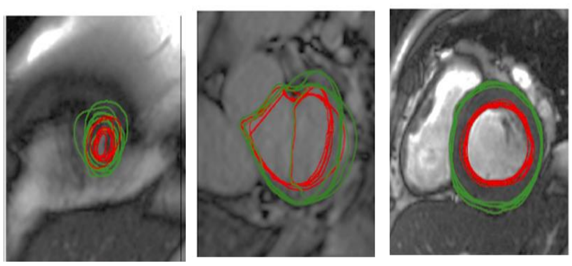
}}

As shown in algorithm 1, the multi-layered perceptron algorithm is composed of artificial neurons, including hidden layers for the problems of binary classification. For each neuron, a perceptron uses an activation feature. Hence, the Multilayer perceptron's are biological neuronal algorithms which use the perceptron in artificial neurons. The activation function determines each neuron's weighted inputs and reduces the number of layers to two layers, by varying the weights that are assigned to a perceptron.

Preposition 3: Mathematical Model for prognosis

For the hypothesis in this paper mathematical formula has been derived for the determination of prognosis, i.e., $\tau = f(y_1, \ldots y_q)$, where $y_1, .. y_q$ are clinical features and τ denotes the cardiovascular event in the patient with heart failure, and the previous study shows less probability in prediction, as shown in the Figure.6(a,b,c) demonstrated positive evidence supporting the hypothesis. In this paper, the predictive ability has been tested and feasibility of the cardiovascular mathematical model in Heart Failure patients to enhance the possibility of creating the mathematic formula to detect the probability of heart disease occurrences. The probability $q_j(t)$ density is therefore defined as follows: for the cardiovascular events of patients j at an elapsed time t the following discharge:

$$q_j(t) = \frac{1}{\tau_j} \exp\left(-\frac{t}{\tau_j}\right) \tag{11}$$



Apex Region　　Left Ventricular Region　　Base Region

Figure .6. **prediction probability of Heart disease analysis**

Meantime the prediction has been elapsed after discharge to patient prehospitalization data based on some of the clinical factors $Y^j = \{y_1^j, \ldots y_q^j\}$ of the patient that is a common subset $Y_W^j \subset Y^j$ of overall patients. The inverse linear relation approximates the dependency primarily:

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$$\tau_j = \frac{1}{\sum_{y_i^j \in Y_W^j} \alpha_i y_i^j + \beta} \qquad (12)$$

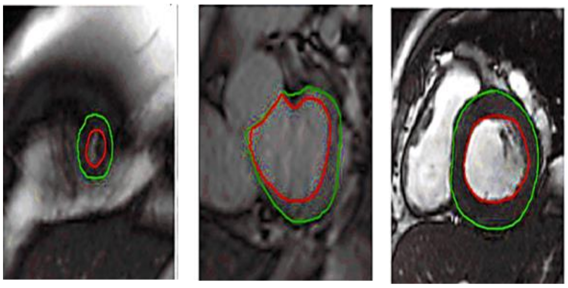
As shown in equation (12) where Y_W^j is a set of values of factors in Y_W for patient j, and β intrinsic frequency. The denominator denotes the expected frequency of heart disease prehospitalization per day, α_i is weight contributing to the ith factor to the frequency. The following equation has been obtained from these two equations,

$$Q(t) = \int_0^\infty q_\tau(\tau)\, q(t) d\tau = \int_0^\infty q_\tau(\tau) \frac{1}{\tau} \exp\left(-\frac{t}{\tau}\right) d\tau \qquad (13)$$

The following natural pre-distribution conjugate has been then used for the unknown $q_\tau(\tau)$:

$$q_\tau(\tau) = \frac{\tau^{-m} \exp\left(-1/\tau \sum_{j=1}^{m} \tau_j\right)}{\int_0^\infty \tau^{-m} \exp\left(-1/\tau \sum_{j=1}^{m} \tau_j\right) d\tau} \qquad (14)$$

As shown in the equation (14) where τ_j is given by dataset D.



Apex Region Left Ventricular Region base Region

Figure .7. **prediction probability of Heart disease analysis**

Finally, the modeling algorithm has been described after several steps of the manipulation with high predictive precision of up to 99 .1%, as shown in Figure.7.(a,b &c). Consequently, equation 11 and 12 have been utilized to the normalized dataset D_M to model the probabilistic process and predict the model variables α_i and β in the equation (11) to increase the following equation (15),

$$K(\alpha_1, \ldots. \alpha_q, \delta) = \ln\left[\prod_{j=1}^{m}\left(\sum_{i=1}^{q} \alpha_i y_i^j + \beta\right)\right] \exp\left\{-\left(\sum_{i=1}^{q} \alpha_i y_i^j + \beta\right)\tau_j\right\} - \lambda\left(\sum_{i=1}^{q} |\alpha_i| + |\delta|\right) \qquad (15)$$

As shown in the equation (15) where the first term is the log-likelihood of the paradigm containing prior equation over D_M. The second term is called the L1 regularization term, which the coefficients of eliminating factors by setting them equal to 0 when the greater hyper-parameter. This term prevents the over-fitting of the model to the dataset by choosing a set of efficient factors Y_W^j from given Y^j.

The mathematical formula for the likelihood of cardiovascular events has been developed. First, there has no significant change in the probability of cardiovascular events per day for patients from their release to their cardiovascular events. To predict the ongoing likelihood of cardiovascular events per day, the following has been defined:

$$\beta = f(y_1, \ldots y_q | \alpha, b) = \alpha^R Y + b = \sum_{i=1}^{q} \alpha_i y_i + b \qquad (16)$$

As shown in the equation (16), where α is the calculated occurrence likelihood of heart disease patients. Thus an exponential formulation is used to describe the likelihood density for cardiovascular events of a patient at an elapsed duration t after release:

$$Q(t|Y;\alpha,b) = \exp(-\beta t) = \exp\{-(\alpha^R Y + b)t\} = \left\{-\left(\sum_{i=1}^{q} \alpha_i y_i + b\right)t\right\} \qquad (17)$$

The survival curve of the patients expressed as the following equation (18) as,

$$Q_{RE}(t|\alpha,b) = \int_{C_T} Q(t|Y;\alpha,b) Q_{RE}(Y) dY = \int_{C_T} \exp\{-(\alpha^R Y + b)t\} Q_{RE}(Y) dY$$

$$= \frac{1}{M_T} \sum_{j \in C_T} \exp\left\{-\left(\alpha^R Y_j + b\right) \cdot t\right\} = \frac{1}{M_T} \sum_{j \in C_T} \exp\left\{-\left(\sum_{i=1}^{q} \alpha_i y_{ji} + b\right) \cdot t\right\} \qquad (18)$$

A known statistic test is the KL-divergence to show the discrepancies between two distributions of probability.

$$LK(Q_T, Q_{RE} | \alpha, b) = \int Q_T(t) \{\ln Q_T(t) - \ln Q_{RE}(t|\alpha,b)\} dY$$

$$= \frac{1}{M_T} \sum_{j \in C_{TT}} \left\{\ln Q_T(t_j) - \ln Q_{RE}\left(t_j | \alpha, b\right)\right\}$$

$$= \frac{1}{M_T} \sum_{j \in C_{RR}} \left[\ln Q_T(t_j) - \ln\left[\frac{1}{M_T} \sum_{j' \in C_T} \exp\left\{-\left(\sum_{i=1}^{q} \alpha_i y_{j'i} + b\right) t_j\right\}\right]\right] \to min \qquad (19)$$

As shown in equation (19) where α and b minimizing these estimates are identified by utilizing the Nelder -mead approach, that is a renowned non-linear optimizing algorithm.

The predicted survival curve has been determined by substituting the above mentioned best value α and b and the clinical feature vectors Y_j of patients in D_q to the following equation (20),

$$Q_{QE}(t|\alpha,b) = \int_{C_Q} Q(t|Y;\alpha,b) q(Y) dY = \int_{C_Q} \exp\{-(\alpha^R Y + b)t\} Q_Q(Y) dY$$

$$= \frac{1}{M_Q} \sum_{j \in C_Q} \exp\left\{-\left(\alpha^R Y_j + b\right) \cdot t\right\} = \frac{1}{M_Q} \sum_{j \in C_Q} \exp\left\{-\left(\sum_{i=1}^{q} \alpha_i y_{ji} + b \cdot t\right)\right\} \quad (20)$$

A mathematical equation has been established that accurately gives the likelihood of the clinical results of patients who are hospitalized and discharged after proper diagnosis. The probability of potential cardiovascular events can be predicted by using the current cardiovascular data. The EDCNN system has been implemented on the Internet of Medical Things Platform (IoMT) for a decision support system, which helps doctors to diagnose heart patient's information in the cloud platform effectively and the Test

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results show that a flexible design with hyperparameters can achieve a precision of up to 99.1 %.

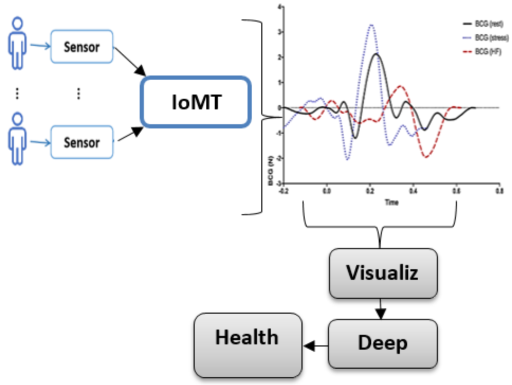
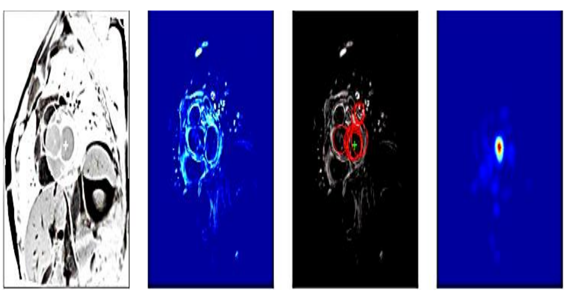


FIGURE .8: Internet of Medical Things for Heart disease analysis

Figure.8. demonstrates the Internet of Medical Things (IoMT) for heart disease prediction. Research has shown that IoT sensors have now been successfully integrated into many different industries, including health care, where the Internet of Medical Things (IoMT) is commonly used. IoMT will monitor heart rates, temperature, blood pressure, oxygen levels, and continuous glucose, and in a ring with an oximeter. This paper proposes an IoMT primarily depends on fitness tracking that can collect all the clinical details of a patient, including blood pressure, heart rate, and ECG, and can send signals with full scientific data to a healthcare practitioner conveying a swift and accurate image of healthcare. Therefore, this paper proposes a simple and effective strategy for this problem in this ultra-modern world where everybody is busy neglecting their small health issues such as high blood pressure, low pulse rate, etc. Further, the test results are discussed as follows,

3. Experimental results and Discussion



9(a) 9(b) 9(c) 9(d)

FIGURE 9: ROI extraction of Heart disease images: a) one slice image with ROI (b)Fourier image (c) circle for slice (d) probability surface across all slices

The experimental results have been performed using the UCI repository datasets. Figure 9 shows the region of interest (ROI) extraction of heart disease images. It is useful to use Fourier analyzes each slice sequence to extract the image, which captures maximum activity at the corresponding heartbeat frequency. The middle of the left ventricle has been eliminated by integrating the transform of the Hough circle with modified kernel-based majority voting with the pulse pressure (PP), as shown in Figure.10. in millimeter of mercury. First, for every image of Fourier. Figure 9(a) is the one slice image with ROI, 9(b) is the Fourier image. Figure 9(c) circle region for a slice and 9(d) shows the likelihood surface across all slices.

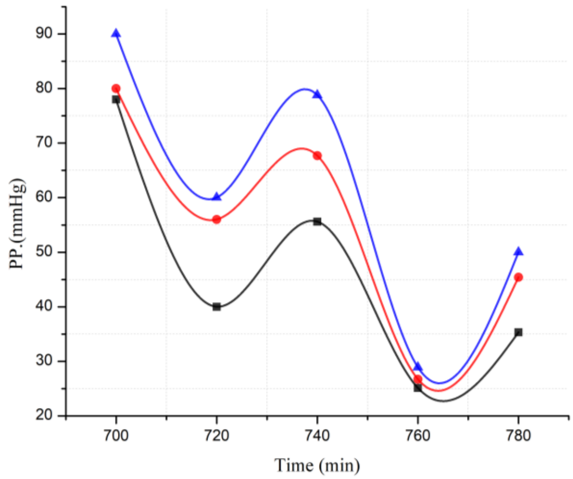


FIGURE 10: Fourier analysis on PP in mmHG

(i) Prediction classification Accuracy Ratio

This paper applies a machine learning technique called the risk prediction classification for risk factors for cardiovascular disease. It seeks to improve the predictive accuracy of cardiopathy risk with a so-called ensemble approach. Associative classification provides high accuracy and high flexibility, even in the handling of unstructured data, compared to traditional classification. The proposed EDCNN model has proved to be a useful tool in the detection of heart disease in medical professionals. An additional stage of feature selection was proposed to improve accuracy. Figure 11 shows the proposed method accuracy ratio.

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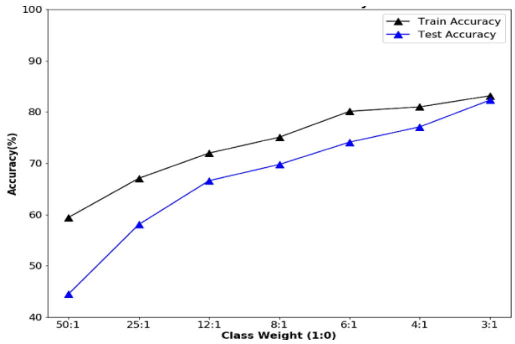
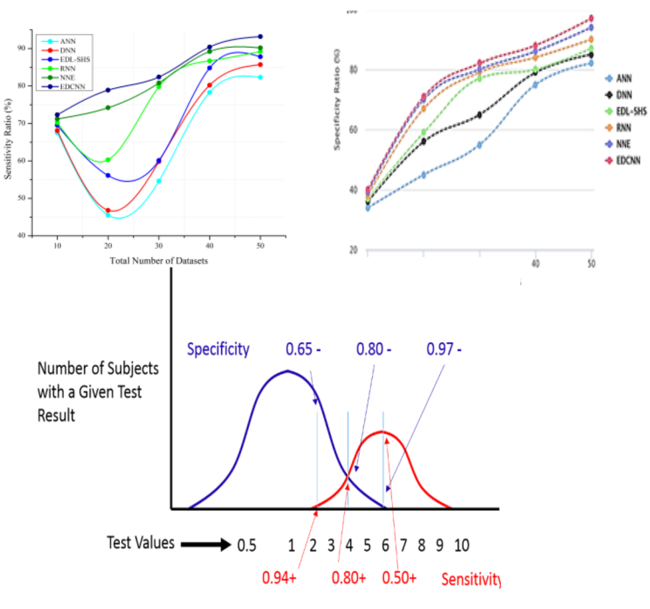


FIGURE 11: **Prediction classification Accuracy Ratio analysis**

(ii) Diagnosis Likelihood Sensitivity and Specificity Ratio

The high sensitivity result of 97.51% is significant because it indicates the likelihood of positive test results in those with heart disease, which means that, with an accurate 93.51% diagnosis in the case of a new patient with undiagnosed heart disease in the clinic. As early and accurate prediction of heart disease is essential for early intervention and extended long-term survival, this high Likelihood sensitivity scoring along with the relatively high 0.8571 and 0.8922 AUC scoring indicates a high accuracy in the diagnosis of heart disease in patients in developing DNN models. DNN models are highly sensitive. The diagnostic accuracy of the heart disease Likelihood specificity ratio is 94.9%.



(c)

FIGURE.12. (a & b) Likelihood Sensitivity/ Specificity Ratio, (c) Test analysis

Figure 12(a and b) shows the Likelihood specificity ratio of the proposed method and (c) Test analysis ratio for the Likelihood Sensitivity/ Specificity. Table 1 shows the Likelihood sensitivity ratio of the proposed EDCNN method.

Likelihood Sensitivity tests positively identified cases of heart disease by the classifier. The Likelihood specificity is used to determine the ability of the classification to test negative cardiac arrest events.

Table 1: Likelihood Sensitivity Ratio numerical analysis

Total Number of Datasets	ANN	DNN	EDL-SHS	RNN	NNE	EDCNN
10	67.5	68.1	69.5	70.2	71.2	72.3
20	45.5	46.8	56.1	60.3	74.2	78.9
30	54.6	59.8	60.1	79.8	80.8	82.4
40	78.3	80.2	84.8	86.7	89.2	90.4
50	82.3	85.7	87.8	89.2	90.2	93.2

(iii) Efficiency Ratio determination

The deep convolutional neural network (or diagnostic) model's efficiency quality depends heavily on the DNN model classification while the training process. In this study, after the completion of the training process, the final weights of the deep neural network prediction model have been loaded from the deep training model subsystem. The dataset is separated into a training set and a test set, and the training data set is used to form individual classifiers. With the test data set, the efficiency of the classifiers is tested. Figure 13 shows the efficiency ratio of the proposed EDCNN method.

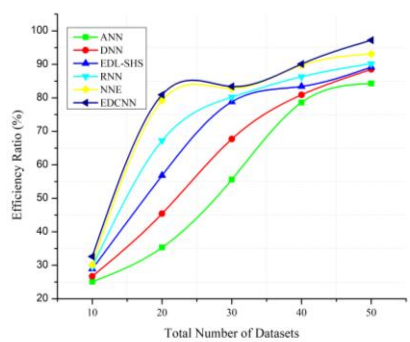


Figure 13: **Efficiency Ratio analysis**

Table 2 shows the efficiency evaluation of the proposed EDCNN method. An Efficient Heart Disease Prediction System with data mining been introduced. The effective EDCNN system is more accurate than other classifier systems. This system can help medical professionals to make decisions efficiently based on the given parameter.

Table 2: Efficiency Evaluation

Total Number of Datasets		ANN	DNN	EDL-SHS	RNN	NNE	EDCNN
10		25.1	26.7	28.9	29.5	30.1	32.6
20		35.3	45.4	56.8	67.2	79.2	80.9
30		55.6	67.7	78.8	80.2	82.8	83.4
40		78.6	80.9	83.4	86.3	89.7	90.1
50		84.3	88.5	89.2	90.2	93.1	97.2

(iv) Performance Ratio

The subsequent performance of the deep learning methods is assessed for the diagnosis of cardiovascular disease in terms of performance measures, including the probability of error in the classification, diagnostic accuracy, precision, sensitivity, specificity. The learning algorithm changes all the DNN classification model weights on the base of the target variable input and output data to achieve the optimal or optimum performance in each iterative training process. Figure.14. demonstrates the performance ratio of the EDCNN method.

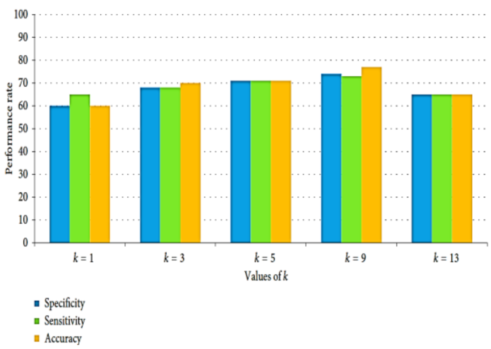


Figure 14: Performance Ratio analysis

4. Conclusion and future scope

This paper developed and evaluated the Enhanced Deep learning assisted Convolutional Neural Network Learning Prediction Models and Classification, depends on diagnostic performance in diagnostic odds ratio, 95 % confidence interval using the sensitivity and specificity of the heart disease. The enhanced deep learning prediction models and classification has been constructed with a deep multi-layer perception equipped to create a secure and improved classification model with non-linear functions and linear, regularization, and falling and binary sigmoid classifications utilizing dedicated learning technologies. The developed prediction models and classification of deep learning can, therefore, allows highly precise and reliable heart disease diagnoses and decrease the number of misdiagnoses that may be of harm to patients. The models can thus be utilized to help patients and healthcare professionals around the world in supporting both global and public health, particularly in developing countries and in resource-constrained areas with fewer cardiac specialists available. The performance has further enhanced by the techniques of feature selection. The feature selection techniques have contributed to the accuracy of the deep learning algorithms. In future, advance artificial intelligence has been planned to incorporate to improve the precision further.

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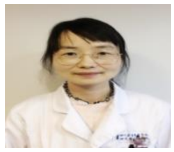

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