Integrated Deep Learning Model for Heart Disease Prediction Using Variant Medical Data Sets

https://doi.org/10.3991/ijoe.v18i09.30801

Syed Anwar Hussainy Fazlur(✉), Senthil Kumar Thillaigovindan
Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu, India
sf1154@srmist.edu.in

Abstract—The Phenomenon of heart disease prediction has been well studied. There exist numerous techniques exist in literature which uses different features and methods. However, the accuracy of predicting heart disease is still a questioning factor. Towards improving the performance of heart disease prediction an efficient Integrated Deep Learning Model with Convolution Neural Network (IDLM_CNN) is presented in this article. The model considers various features from different data sets of lungs, diabetic and clinical features. The integrated model extracts texture features from lung images in form of mass values. Similarly, the blood glucose, BMI and other diabetic features are extracted from diabetic data set. Also, lifestyle features like physical habits, food habits and smoking habits are extracted from clinical data sets. Such features extracted from various data sets are combined and trained with Convolution neural network to support the disease prediction. The method convolves the features of lungs and combines with other features to compute Disease Prone Weight (DPW) towards cardiac disease. Based on the value of DPW, the method predicts the possibility of heart disease. The proposed method increases the performance of disease prediction and reduces the false ratio.

Keywords—CNN, heart disease, multi variant data set, DPW, lung images, clinical data set, disease prediction

1 Introduction

Survival of the mankind is under scrutiny of different forms of threats. The diseases are the one which is being identifies as the threat which target the human society. Every year different diseases are identified which affect the human society greatly. Such diseases are mostly produced by some sort of bacteria and virus. Most of the diseases are harmless and would be cured or eradicated easily. But some of them are harmful for the health of humans and cannot be cured completely. On the other side, apart from diseases produced by viruses and bacteria, there are diseases which are at the organ level. Such diseases affect the functioning of human organs.

The heart is the most important organ of any human which pumps the blood through millions of blood vessel to supply blood to the other organs of human. The veins carry the blood and water to the parts of human body, because of both water and blood requires the functioning of human body. The veins not just carry the blood but also carry the oxygen to the organs of human body. The entire process is carried by two different organs namely heart and lungs. The lungs [1] is responsible for pumping the oxygen where heart is responsible for pumping the blood. So, for a complete functioning of human body, the functioning of both organ is more important. In ancient days, the average lifetime of human was about hundred plus years where the lifetime of modern human society is reduced up to 70 years. This is due to the changing lifestyle and other habits of human because the food, physical working and etc are total changed from the ancient days. This introduces various diseases to the human, heart failure and heart diseases are one among them. Any disease can be highly curable or controllable when it is being detected or diagnosed at the early stage.

The presence or the possibility of heart disease can be predicted according to different features and methods. To sort out the heart disease, there are number of approaches available. For example, the heart disease can be predicted by using the cardiac data set which contains set of ECG (Electro Cardiogram) data sets. By analyzing the ECG waveform obtained from various patients who affected by cardiac based diseases, the affected cases of cardiac can be evaluated [7]. To perform this different classification algorithms are available. The K nearest neighbor algorithm extract the features of ECG waveform like QRS signal, P-wave, R-wave and by computing the Euclidean distance the input sample has been classified as positive or negative. Similarly, the problem of heart disease prediction has been approached using PCA (Principal Component Analysis) which select the feature towards heart disease prediction. The Support Vector Machine (SVM) has been used towards heart disease prediction by computing support values according to the features available in the ECG waveform. Similarly, there are so many approaches available to perform the prediction of heart disease according to the ECG data set given.

The theory here is the relation between the conditions of lungs in reaching heart disease. The article is focusing on identifying the condition of lungs and how it supports the arrival of heart disease in any person. In reality the person who has the smoking habit has higher risk of getting heart attack and heart diseases. So, by analyzing the lung images of human, the possibility of heart disease can be predicted. So, to accelerate the functionalities of heart disease prediction, the lung features can be integrated with the cardiac features. On the other side, considering just cardiac data is not enough in identifying the risk of heart disease but the diabetic features has great relationship with heart diseases [5]. When a person affects by diabetes the veins of heart becomes hard in long time and lost their strength. Also, the arrival of diabetes opens the gate for the entry of many other diseases like blood pressure. When the pancreas does not produce the insulin required for the destroying of calories, then they form cholesterol and fat in the blood veins which suffocates the blood flow. All these encourage the arrival of heart diseases in human. By considering all these, the proposed model incorporates or integrates various medical data sets in predicting the heart disease.

The medical data sets have variety of information and the dimension is higher. Also, when you consider the lung data set, the dimension of lung data set will be huge and classifying the input sample using lung image would suffer with dimensionality problem. When the dimensionality is higher, it claims higher time complexity and would face higher false ratio. To solve this problem, the convolution neural network can be used. The neural network are used in various scientific problems which is composed of many neurons constructed in different layers where each neuron perform a dedicated job to estimate the weight measure towards any class and propagates the weight to the next layer. Finally, a output is generated according to the weight measures computed. But when the dimensionality of feature is higher, then there is huge chance of over fitting and false ratio. To handle this issue, the convolution neural network are incorporated in this proposed model which convolve the lung features to produce one dimensional limited feature and combine with other features obtained from various data sets to perform disease prediction. This article details how the features of various data sets are used and how they support the improvement of heart disease prediction in detail.

2 Related works

There are number of approaches discussed in literature towards heart disease prediction. This section details set of methods related to the problem.

Mohan et al [1] proposed a clever strategy that targets tracking down critical elements by applying AI procedures bringing about working on the precision in the expectation of cardiovascular infection. The expectation model is presented with various blends of highlights and a few known characterization methods. The technique produce an improved exhibition level forecast for coronary illness with the half and half irregular backwoods with a straight model (HRFLM).

Heart Disease Prediction model presented by Fitriyani et al [2], it is formulated by Density-Based Spatial Clustering of Applications with Noise to detect and eliminate the outliers, a hybrid Synthetic Minority Over-sampling Technique-Edited Nearest Neighbor to neutralize the training data and XGBoost to predict heart disease.

Pan et al [3] has augmented his work on the Internet of Medical Things Platform (IoMT) for decision support systems which helps doctors to successfully idealize heart patient's information in clouds and access easier.

In order to identify the Heart diseases through feature selection problem, a fast novel fast conditional mutual information feature selection algorithm was proposed by Li et al [4]. The feature selection algorithms are used for weight analysis, to increase the classification accuracy and reduce the execution time of classification system. Furthermore, the leave one subject out cross-validation method has been used for learning the best practices of model assessment and for hyper parameter tuning.

Guo et al [5] through his work finds the risk factors leading to cardiovascular disease can be actionised. An optimality of prime variables showed with the IoMT platform, for data analysis. This Shows that cognitive Heart diseases grows higher in end days of life cycle with tangible blood flows.

B. Wang et al [6] proposes a multi-task deep and wide neural network (MT-DWNN) for predicting fatal complications during hospitalization. This method has analyzing an impact renal dysfunction plays a vital in life Heart failure patients.

The Model proposed by Khan et al [7] is to judge cardiovascular disease more accurately employing a Modified Deep Convolutional Neural Network (MDCNN). The smart watch and monitor device that's attached to the patient monitors the pressure level and ECG. The MDCNN is used for classifying the received sensor data into normal and abnormal. The performance of the system is analyzed by comparing the proposed MDCNN with existing deep learning neural networks and logistic regression.

Xiao et al [8] analyzed the performance of Heart disease by separation based on the dice coefficient compared between the two datasets. The results shows that the model training effect of the centerline preprocessing is superior to the original data.

A new Hybrid Model was developed by Chang et al [9] through an hybrid XGBSVM (Extended Gradient Boosting Support vector Machine) is to predict whether hypertensive patients will live with cardiapathy within three years. The ultimate aim is reduce the cost factor affected and long breath time and take some preventive measures.

J. Wang et al [10] proposed a two level stacking based model is intended within which, as base-meta-level. The predictions of base-level classifiers is chosen. The correlation coefficient are first calculated to sort out the classifier with very low correlation. Then enumeration algorithm is employed to beast out the simplest ensemble method to proceed higher.

A brand new method to predict MHR With the usage of functional data analysis (FDA) proposed by Matabuena et al [11]. It uses rate data gathered every 5 seconds during a coffee intensity, sub-maximal exercise test. FDA allows the employment of all the knowledge recorded by monitoring devices within the variety of a function, reducing the number of data needed to generalize a model, besides minimizing the curse of dimensionality.

The better higher cognitive process by the biomarkers for Analyzing heart condition through Blood and Saliva samples was Proposed by Tripoliti et al [12] when managing Heart Failure patients. The devices are either commercially available or within the style of new prototypes.

To improve the prediction accuracy, Luo et al [13] proposes startup method on cardiac magnetic resonance (CMR). Next, they develop a new network structure for end-to-end Left Ventricular volume estimation. Finally, they gatrich the leading capacity of different clips and propose a fusion strategy to enlighten the expected.

Nowadays Non-Communicable Disease leads the top position of person wherein prediction is flaw of analysis, here Ferdous et al [14] proposes a singular gadget gaining knowledge of primarily based totally fitness CPS framework that addresses the project of successfully processing the wearable IoT sensor records for early danger prediction of diabetes for example of NCDs.

Rodrigues et al [15] applies a Structural Equation Modelling the use of Partial Least Square Method become used for the evaluation of data in their work. The effects have found out that besides for age, frame mass index and systolic blood strain all of the relaxation of the elements had a sizeable fine affiliation with high blood pressure and coronary coronary heart disease.

Diwakar et al [16] proposed a version which incorporates an evaluate of the class strategies for system studying and photo fusion which have been established to assist healthcare specialists perceive coronary heart disease. They start with the system studying quick and summarize descriptions of the especially used class strategies for diagnosing sicknesses of coronary heart.

El Hamdaoui et al [17] tailors his work by ensembling Random Forest with AdaBoost and produces a higher accuracy rate in predicting the heart diseases through globalized data sets by incorporating 10 cross validation for betterment.

The ECG plays as a best feed to find out the Cardio vascular diseases by applying Deep Learning Methods such as Artificial Neural Network and gives higher Prediction while Extracting the peak features QRS Peaks in his work by Nayan et al 2020 [18].

All the above discussed approaches suffer to achieve higher performance in heart disease prediction.

3 Integrated deep learning with convolution neural network (IDLM_CNN) based heart disease prediction model

The proposed integrated deep learning disease prediction model fetches various data sets. The lung data set contains different texture values representing the range of infection and the clinical data set contains different heart functioning features. The diabetic data set contains different features of diabetic patients. The features from the above mentioned data sets are extracted and trained with convolution neural network. Further at the classification phase, the method extracts the same set of features and estimates the disease prone weight (DPW) for the input sample. According to the value of DPW, the method performs heart disease prediction. The detailed approach is discussed in this section.

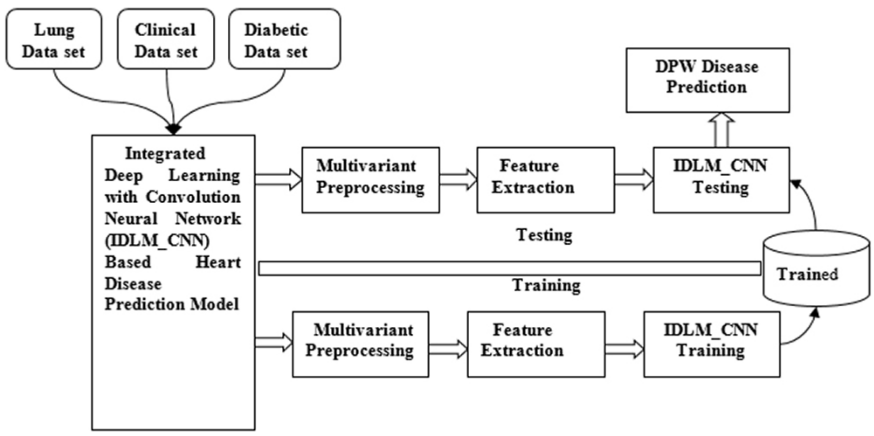

Fig. 1. Architecture of proposed IDLM_CNN prediction model

The functional architecture of proposed IDLM_CNN heart disease prediction model is presented in Figure 1, where the functional components of the model are discussed in detail in this section.

3.1 Multi variant preprocessing

The data set given is preprocessed in several stages. The method first fetches the lung data set and for each lung image L, the method applies Fixed Window Adaptive Median Filtering, which filters the noise in the lung image by computing the median value at different diagonal and axial coordinates. It has been applied by splitting the window into four different diagonal windows. At each diagonal window, the method estimates the gray mean. Based on the median value, the nearest median is selected for the pixel and adjusted. This eliminates the noise in the image and sharpens the image to improve the image quality. Second, the clinical and diabetic data sets are read and set of features are identified. Further, each tuple of the data set are fetched and verified for the availability of feature in each slot. If any feature is missing with any of the tuple, then it has been considered as noisy and eliminated from the data set.

Algorithm

Given: Lung Data Set LDS, Diabetic Data Set Dds, Clinical Data set CLDS.
Obtain: Preprocessed LDS, DDS, CLDS
Start
    Read LDS, DDS, CLDS
    Initialize window size Ws.
    For each lung image l
        I = Apply fixed window adaptive median filtering on I.
        For each pixel p
                For each window ws
        $\text{Measure diagonal mean Dmean} = \sum_{i=1}^{size(Ws)} I(Ws(i), Diagonal) / size(Ws)$
        $\text{Measure axial mean Amean} = \sum_{i=1}^{size(Ws)} I(Ws(i), \text{Axial Neighbors}) / size(Ws)$
        Choose the closest mean and adjust pixel value
                End
        End
    End
        Fetch clinical and diabetic data set.
        Identify the feature lists Felist.
        $Felist = \sum_{i=1}^{size(DDS)} DDS(i).Feature \ni Felist \cup \sum_{j=1}^{size(CLDS)} CLDS(j).Feature \ni Felist$
    For each tuple t
                If $\overset{size(CDS\,\&\,CLDS)}{\underset{i=1}{DDS(t) \ni \forall Felist\ Or\ CLDS(t) \ni \forall Felist}}$ then
                Remove the tuple from data set.
        End
    End
Stop

The above discussed algorithm represents how the preprocessing on multi variant data set is performed. The method fetch lung data set and removes noise from the lung images by applying fixed window median. Similarly, the clinical and diabetic data sets are verified for their completeness and removed from the data set.

3.2 Feature extraction

The feature extraction phase read the lung image set has been read and from the lung image, the method applies Gray Mass Approximation approach to identify the region of interest ROI. Once the ROI is identified, then the texture has been extracted according to the coordinates identified. Similarly, the features of diabetes like BMI, Fasting sugar, Meal sugar, HbA1C are extracted. From the clinical data set, the method extracts blood pressure, heart rate, temperature, lifestyle feature like food, smoke, physical exercise, vomiting, cholesterol are extracted. Such features extracted are used in CNN Training and testing to support heart disease prediction.

Algorithm

```
Given: LDS, CLDS, DDS.
Obtain: Texture set Ts, Heart Rate set Hs, Diabetic Feature set DFS, and
        Clinical Feature set CFS.
Start
        Read LDS, CLDS, DDS.
        For each lung image l
                MinG = Identify minimum gray scale value
                MinG = Min_{i=1}^{size(l)} (l(i).value)
                MaxG = Identify maximum gray scale value
                MaxG = Max_{i=1}^{size(l)} (l(i).value)
                Hist = Generate histogram of gray scale values.
                Hlist = Find first two higher grayscale value.
                Choose the pixels and mark the region as ROI
                ROI = Σ_{i=1}^{size(l)} l(i).value ∈ Hlist
                Texture T = Extract the texture of ROI.
                Add to texture set Ts = Σ (Textures ∈ Ts) ∪ T
End
        From each tuple T of Diabetic data set DDS
        Extract blood sugar bs, after meal sugar Ams, before meal sugar Bms,
        BMI, HbA1C.
                DFS = {BS, Ams, BMS, BMI, HbA1C}∈ T
End
        For each tuple T of Clinical Data set CLDS
        Extract pressure Bp, Heart Rate Hrate, Vomiting V, Smoke S,
        physical exercise Pe.
                CFS = {Bp, Hrate, V, S, Pe} ∈T
End
        Stop
```

The feature extraction algorithm extracts various features from clinical, diabetic, and lung data sets. The features extracted has been converted in to feature set and added to the set to support training and testing.

3.3 IDLM_CNN training

The proposed integrated deep learning model with convolution neural network towards disease prediction algorithm performs training in two different stages. The feature set obtained are read and the features of lung image in form of texture are applied with first level convolution which reduces the entire feature in to one dimensional array and the rest of the features are feed to the neurons. The network is initialized with number of neurons and each neuron has been assigned with specific lung texture, diabetic and clinical data set. The texture features obtained from lung images are framed into matrix which has been convolved by the neurons to reduce the feature dimension. This has been performed by applying the convolution operation at the selective window region and the remaining features are given as it is. The neurons are feed by two different matrices where the first one forms the texture obtained from the lung image where the second combines both clinical and diabetic data set. The second feature matrix has been used at the ReLU layer to estimate the similarity measures. The network is framed with seven layers which includes input and output layer. The convolution layer applies convolution operation on the texture feature of lung and the pooling layer estimates weight measure on various features. The trained network has been used to perform testing towards disease prediction.

3.4 IDLM_CNN testing

The test samples given have been considered for testing. With the trained network, the method read the samples given and applies preprocessing on multivariate data set. Further, feature extraction is performed which extracts various features. The lung, diabetic and clinical features being extracted are applied with CNN network which convolve the texture feature to convert to a single dimension feature. With the features converted, the model estimates different metrics in terms of support measures. The neurons estimate the support measures and produce them at the output layer. The neurons compute the cardiac lung disorder support (CLDS) according to the lung features obtained from the test lung image and the features of trained lungs as follows:

$$\mathrm{CLDS} = \sum_{i=1}^{size(Ts)} Dist\left(T.Texture, \frac{\begin{matrix} \mathrm{size(Textures)} \\ \sum \mathrm{Textures(i).value} > 235 \\ \mathrm{i} = 1 \end{matrix}}{\mathrm{size(Textures)}} \right) / \mathrm{Size(Ts)} \tag{1}$$

The method computes the value of Cardiac Diabetic disorder score (CDDS) as follows:

$$\mathrm{CDDS} = Dist\left(T, \frac{\sum_{\mathrm{i=1}}^{\mathrm{size(DDs)}} \frac{\mathrm{DDS(i).Bs} > 300}{\mathrm{size(DDS)}} + \frac{\mathrm{DDS(i).BMI} > 6}{\mathrm{size(DDS)}} + \frac{\mathrm{DDS(i).BMS} > 200}{\mathrm{size(DDS)}} + \frac{\mathrm{DDS(i).AMS} > 400}{\mathrm{size(DDS)}}}{\mathrm{size(DDS)}} \right) \tag{2}$$

Finally the Cardiac clinical disorder score (CCDS) is measured as follows:

$$CCDS = Dist\left(T, \frac{\sum_{i=1}^{size(CDs)} \frac{CDS(i).Bp > 170}{size(CDS)} + \frac{CDS(i).PE < 0}{size(CDS)} + \frac{CDS(i).S < 0}{size(CDS)}}{size(CDS)}\right) \quad (3)$$

The neurons of CNN network produces such score values at the output layer which has been used to perform disease prediction.

3.5 DPW disease prediction

The disease prediction algorithm receives the input test sample and perform pre-processing and feature extraction. Extracted features are pass through CNN network designed which computes different disorder scores like CLDS (cardiac lung disorder score), CDDS (cardiac diabetic disorder support) and CCDS (Cardiac clinical disorder support). Using these support measures, the method computes the disease prone weight (DPW) to perform disease prediction. Estimated value has been used in concluding the possibility of cardiac disease.

Algorithm

Given: Diabetic data set DDS, Lung data set LDS, clinical data set Clds.
Obtain: Boolean
Start
    Read DDS, LDS, CLDS
    Perform preprocessing
    {T, DFS, CFS,CLFS} = Feature Extraction (DDS, LDS, CLDS}
    {CLDS, CDDS, CCDS} = Perform CNN Testing.
    Compute $DPW = \frac{CLDS}{CCDS} \times CDDS$
    If DPW>Th then
        Return true
    Else
        Return false
    End
Stop

The disease prediction algorithm estimates the disease prone weight towards cardiac disease according to different support measures obtained on cardiac, clinical, lung and diabetic data features. According to the features obtained, the method computes the value of disease prone weight. Based on the value of DPW the method performs disease prediction.

4 Results and discussion

The proposed integrated deep learning model based heart disease prediction has been implemented in Matlab and its performance is analyzed in various factors. The performance of IDLM_CNN is measured on different parameters according to different data sets.

Table 1. Details of dataset

Constraint	Value
Tool Used	Matlab
Data set	Lung, Clinical, Diabetic
Number of Disease class	3
Disease Classes	Bradycardia, Tachycardia, Myocardia
Number of Samples	100,000

The performance of the methods at disease prediction against heart disease has been measured according to the data set presented above in Table 1. The results obtained from various approaches are discussed in this section. The performances of the methods are measured on how various diseases according to the data sets available. The data set has been constructed by collecting various images

Table 2. Performance on heart disease prediction accuracy

Methods	Bradycardia	Tachycardia	Myocardia
XGBSVM	72	76	79
RERF-ILM	76	79	83
MDCNN	79	84	87
IDLM_CNN	88	93	98

The accuracy on predicting the disease achieved by various approaches are measured and presented in the above Table 2. The IDLM_CNN approach achieved higher accuracy in predicting the disease than other approaches.

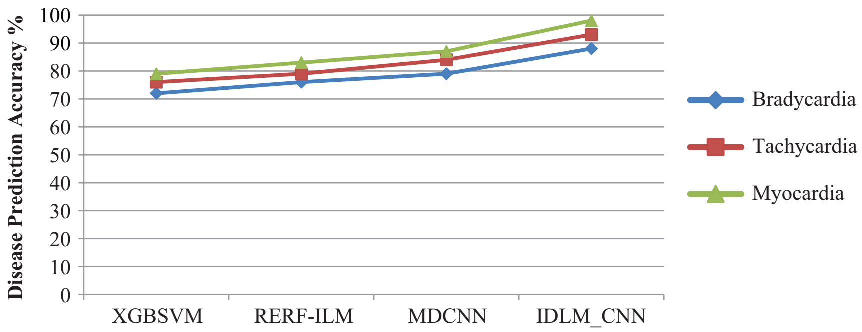

Fig. 2. Analysis on disease prediction accuracy

The performance of identifying the heart disease prediction has been measured by varying number of data points and presented in Figure 2. The IDLM_CNN model achieved higher disease prediction accuracy apart from others.

Table 3. Analysis on false ratio

False Ratio on Disease Prediction			
Methods	**Bradycardia**	**Tachycardia**	**Myocardia**
XGBSVM	28	24	21
RERF-ILM	24	21	17
MDCNN	21	16	13
IDLM_CNN	12	7	2

The ratio of false disease prediction is measured and compared in Table 3, where the IDLM_CNN model has generated only less false ratio than others.

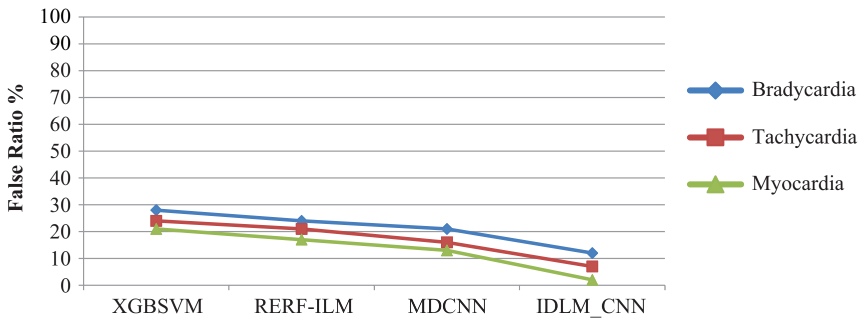

Fig. 3. False classification ratio analysis

The ratio of false prediction generated by various approaches are counted and plotted in Figure 3. Among them the IDLM_CNN model has generated only fewer values.

Table 4. Analysis on time complexity

Time Complexity in Millie Seconds			
Methods	**Bradycardia**	**Tachycardia**	**Myocardia**
XGBSVM	73	79	89
RERF-ILM	69	74	83
MDCNN	56	69	78
IDLM_CNN	14	21	29

The time complexity introduced by different methods are measured and presented in Table 4, which shows the proposed IDLM_CNN approach has produced less time complexity than other techniques.

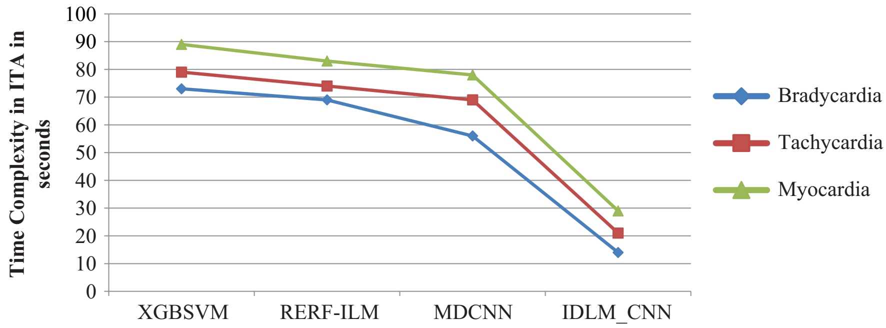

Fig. 4. Analysis in time complexity

The time complexity incurs by different methods in predicting the disease is measured and presented in Figure 4. The proposed IDLM_CNN approach has produced less time complexity other methods.

5 Conclusion

The proposed integrated deep learning model based heart disease prediction scheme uses different data sets like diabetic, lungs and clinical data set. From different data set the method extracts various features like texture, heart rate, blood sugar, after and before meal sugar, BMI, Physical exercise, smoking, and other features. The features extracted are trained with neural network which applies convolution on texture feature and the rest of the features are feed through neural network towards training the network. At the test phase, the same set of features are extracted, the neurons estimates various support measures on different class of features. Using the measures estimated the method compute the value of disease prone weight (DPW) based on which disease prediction is performed. The method improves the performance on disease prediction and reduces the false ratio.

6 References

[1] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective Heart Diseaserediction Using Hybrid Machine Learning Techniques," *IEEE Access*, vol. 7, pp. 81542–81554, 2019, https://doi.org/10.1109/ACCESS.2019.2923707

[2] N. L. Fitriyani, M. Syafrudin, G. Alfian, and J. Rhee, "HDPM: An Effective Heart Disease Prediction Model for a Clinical Decision Support System," *IEEE Access*, vol. 8, pp. 133034–133050, 2020, https://doi.org/10.1109/ACCESS.2020.3010511

[3] Y. Pan, M. Fu, B. Cheng, X. Tao, and J. Guo, "Enhanced Deep Learning Assisted Convolutional Neural Networkfor Heart Disease Prediction on the Internet of Medical Things Platform," *IEEE Access*, vol. 8, pp. 189503–189512, 2020, https://doi.org/10.1109/ACCESS.2020.3026214

[4] J. P. Li, A. U. Haq, S. U. Din, J. Khan, A. Khan, and A. Saboor, "Heart Disease Identification Method Using Machine Learning Classification in E-Healthcare," *IEEE Access*, vol. 8, no. Ml, pp. 107562–107582, 2020, https://doi.org/10.1109/ACCESS.2020.3001149
[5] C. Guo, J. Zhang, Y. Liu, Y. Xie, Z. Han, and J. Yu, "Recursion Enhanced Random Forest with an Improved Linear Model (RERF-ILM) for Heart Disease Detection on the Internet of Medical Things Platform," *IEEE Access*, vol. 8, pp. 59247–59256, 2020, https://doi.org/10.1109/ACCESS.2020.2981159
[6] B. Wang *et al.*, "A Multi-Task Neural Network Architecture for Renal Dysfunction Prediction in Heart Failure Patients with Electronic Health Records," *IEEE Access*, vol. 7, pp. 178392–178400, 2019, https://doi.org/10.1109/ACCESS.2019.2956859
[7] M. A. Khan, "An IoT Framework for Heart Disease Prediction Based on MDCNN Classifier," *IEEE Access*, vol. 8, pp. 34717–34727, 2020, https://doi.org/10.1109/ACCESS.2020.2974687
[8] C. Xiao, Y. Li, and Y. Jiang, "Heart Coronary Artery Segmentation and Disease Risk Warning Based on a Deep Learning Algorithm," *IEEE Access*, vol. 8, pp. 140108–140121, 2020, https://doi.org/10.1109/ACCESS.2020.3010800
[9] W. Chang, Y. Liu, X. Wu, Y. Xiao, S. Zhou, and W. Cao, "A New Hybrid XGBSVM Model: Application for Hypertensive Heart Disease," *IEEE Access*, vol. 7, pp. 175248–175258, 2019, https://doi.org/10.1109/ACCESS.2019.2957367
[10] J. Wang *et al.*, "A Stacking-based Model for Non-invasive Detection of Coronary Heart Disease," *IEEE Access*, vol. 8, pp. 37124–37133, 2020, https://doi.org/10.1109/ACCESS.2020.2975377
[11] M. Matabuena, J. C. Vidal, P. R. Hayes, M. Saavedra-Garcia, and F. H. Trillo, "Application of Functional Data Analysis for the Prediction of Maximum Heart Rate," *IEEE Access*, vol. 7, pp. 121841–121852, 2019, https://doi.org/10.1109/ACCESS.2019.2938466
[12] E. E. Tripoliti *et al.*, "Point-of-Care Testing Devices for Heart Failure Analyzing Blood and Saliva Samples," *IEEE Rev. Biomed. Eng.*, vol. 13, pp. 17–31, 2020, https://doi.org/10.1109/RBME.2019.2905730
[13] G. Luo, S. Dong, K. Wang, W. Zuo, S. Cao, and H. Zhang, "Multi-views Fusion CNN for Left Ventricular Volumes Estimation on Cardiac MR Images," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 9, pp. 1924–1934, 2018, https://doi.org/10.1109/TBME.2017.2762762
[14] R. Ferdousi, M. A. Hossain, and A. El Saddik, "Early-Stage Risk Prediction of Non-Communicable Disease Using Machine Learning in Health CPS," *IEEE Access*, vol. 9, pp. 96823–96837, 2021, https://doi.org/10.1109/ACCESS.2021.3094063
[15] L. L. R. Rodrigues *et al.*, "Machine Learning in Coronary Heart Disease Prediction: Structural Equation Modelling Approach," *Cogent Eng.*, vol. 7, no. 1, p. 1723198, 2020, https://doi.org/10.1080/23311916.2020.1723198
[16] M. Diwakar, A. Tripathi, K. Joshi, M. Memoria, and P. Singh, "Latest Trends on Heart Disease Prediction Using Machine Learning and Image Fusion," *Mater. Today Proc.*, vol. 37, pp. 3213–3218, 2021. https://doi.org/10.1016/j.matpr.2020.09.078
[17] H. El Hamdaoui, S. Boujraf, N. E. H. Chaoui, B. Alami, and M. Maaroufi, "Improving Heart Disease Prediction Using Random Forest and AdaBoost Algorithms," *Int. J. online Biomed. Eng.*, vol. 17, no. 11, pp. 60–75, 2021, https://doi.org/10.3991/ijoe.v17i11.24781
[18] N. A. Nayan et al., "Cardiovascular Disease Prediction From Electrocardiogram by Using Machine Learning," *Int. J. online Biomed. Eng.*, vol. 16, no. 7, pp. 34–48, 2020, https://doi.org/10.3991/ijoe.v16i07.135692

7 Authors

Syed Anwar hussainy Fazlur is a Research Scholar from the Department of Computing Technologies, SRM Institute of Science and Technology, Chennai, India. Doing His Doing his research in the area of Artificial Intelligence.

Senthil Kumar Thillaigovindan is an Associate Professor, from the Department of Computing Technologies, SRM Institute of Science and Technology, Chennai, India. Completed his Doctorate in the year 2019. Published more than 20 Papers in the Indexed Journals.

Article submitted 2022-03-12. Resubmitted 2022-05-07. Final acceptance 2022-05-08. Final version published as submitted by the authors.