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HEART DISEASE DETECTION USING DEEP LEARNING IN HEALTHCARE

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ABSTRACT

In recent years, healthcare prediction has played an important role in saving lives. Artificial intelligence for understanding crucial data relations and transforming them into valuable data for prediction is increasingly used in the healthcare sector. The healthcare sector is growing fast due to Artificial Intelligence. Deep ML models playing a significant role in disease detection and pattern identification. These models even can help to diagnose that disease which cannot be detected easily by human beings. By applying deep learning models to Electronic Health Records, an experimental comparative research design is implemented using DNN, MLP, CNN, LightGBM, TabNet, and CatBoost models. The performance of each model is evaluated and compared using different metrics: Accuracy, F1 Score, and ROC AUC. The ensemble model is found significant in terms of Accuracy and F1 Score, whereas LightGBM and CatBoost are found effective in terms of ROC AUC. The study concludes that to detect heart disease using patient data on key health indicators, Machine Learning and Deep Learning methods—especially the ensemble model—are significant. The main goal of this research is to decide which patient has the maximum probability of heart disease based on several medical values. To predict the probability of heart disease, the author created an ensemble model using the patient's medical records.

Keywords: Machine Learning, Artificial Intelligence, Deep Learning, Healthcare Sector, Heart Disease, CNN, DNN, MLP, Transformer, Healthcare

1. INTRODUCTION

Blood veins obstruction, heart attacks that cause chest pain, heart failure, and other heart disease that may give rise to death or other major problems. These are all the Symptoms Heart disease (CVD) [1]. In 2015, 15 million people died because of it, and it first rank among the top ten reasons of death in past 15 years [2]. A survey conducted in January 2017 found that cardiovascular infections are the leading cause of death worldwide. By 2030, the WHO expects that, heart disease will be the main cause of death over the world, expecting 17.9 million deaths every year [3].

The mortality ratio from coronary heart disease also rises every year. By 2030, the population will reach 23.6 million. The prevalent cardiovascular problems include peripheral arterial occlusive disease, strokes, coronary heart disease, congenital cardiovascular malformation vascular illness, thrombophlebitis, transient ischemic attacks (TIA), heart disease, and pulmonary embolism [4]. Another risk factor complicates the diagnosis of heart disease, such as hypertension, excessive cholesterol value, high bp, and irregular pulse rate. To reduce this toll, early identification of CVD is essential.

Healthcare products that result at a reasonable cost must be produced. Additionally, the healthcare institutions are searching for affordable, simple clinical tests. Organizations can serve the requirements of millions of people globally by creating a decision support system for the diagnosis of different diseases. Research in many domains, including health, has benefited from the quick development of DL and ML algorithms.

These algorithms are trained with the aid of extensive medical diagnosis data. These algorithms can be used to create a clinical assistance system that improves accuracy while lowering costs [4].

Machine learning algorithms can use a variety of clinical data to classify patients' risk profiles. Certain characteristics, such as age, sex, and genetics, are beyond the patient's control, whereas characteristics like bp, drinking patterns and smoking, are [5]. To distinguish between patients who are healthy and those who are not, the suggested algorithm combines these characteristics. The research paper is organized as follows: Current methods for predicting cardiac disease using machine learning are covered in Section II. Suggested architecture is included in Section 3. Implementation of the proposed model and results are covered in Section IV.

2. LITERATURE REVIEW

Decision tree and support vector machine were proposed by S. Radhi Meenakshi [4] for the classification of cardiac disease. So author concluded that the performance of decision tree classifier is better in terms of accuracy than SVM based on a confusion matrix.

R.W. Jones et al. suggested a neural network-based approach to predict heart disease [6]. They used a self-applied questionnaire to train the neural network. The model is train using back propagation algorithm. It had three hidden layers. They obtained 98% accuracy on the dataset. Using the Dundee rank factor score the architecture is validated.

The effectiveness of backpropagation and evolutionary algorithms for neural network architecture training was compared by Ankita Dewan et al. [7]. They concluded that backpropagation methods outperform other algorithms with the least amount of error on the dataset. Learning vector quantization techniques was put forth by SY Huang et al. [8] for ANN training. For training the model, they used 13 clinical features. The accuracy achieved on the dataset is around 80%.

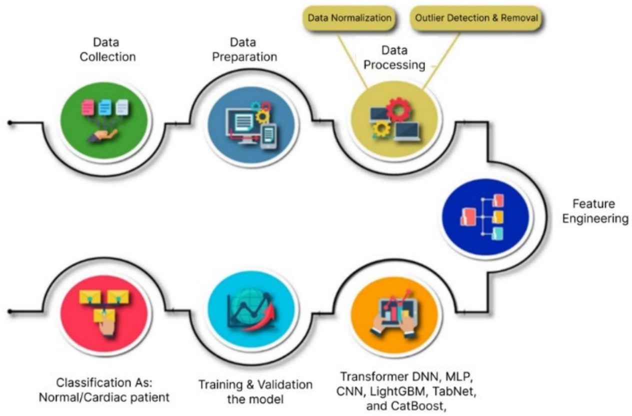
The new ANN is designed by Jayshril S. Sonawane et al. [9] that can be built via random order incremental training and a vector quantization technique. Thirteen features are used to train the model on the dataset and achieve accuracy around 86%. Various classification techniques, such as Multilayer Perceptron, C4.5, Sequential Minimal Optimization, feed-forward backpropagation were employed by Majid Ghonji Feshki et al. [10]. On the dataset the PSO algorithm is implemented using neural network. They concluded that the model had at about 91.94%. accuracy.

The literature addressed heart disease prediction in several methods. Using the same inputs as our study, [10] measured wearable smartphones and utilized SVM, Functional Trees, Naïve Bayes to predict the likelihood of cardiac diseases with 84.6% accuracy. Furthermore, Naïve Bayes was used in [11] on the same dataset and achieved 86.5% accuracy which is a slightly greater than the previous one.

Chaurasia et al. [12] have suggested data mining viewpoints for identifying cardiac issues in human bodies. This strategy has made use of the WEKA machine learning tool and bagging, J-48 and Naïve Bayes. Machine learning is done in the UCI lab. The dataset for heart disease has 13 variables, 313 features for prediction. Regarding classification accuracy, J48 gives 84.34%accuracy which is comparatively less than Bagging. Bagging offers 85.34%, and Naïve Bayes offers 82.30%. To enhance the dataset's ability to forecast heart illnesses, R. Sharmila et al. suggested using data techniques. An accuracy of 85% was provided by SVM. In terms of accuracy, parallel SVM is more accurate than sequential SVM.

Rubini P, et al explained link between diabetes and heart disease [14]. The author finds relationship between two and mentioned also mentioned how much diabetes affects heart disease. Increasing the number of parameters can improve performance. Researcher [1] used mobile based iOS application to predict heart disease using healthcare data and achieved 72.7% accuracy.

They suggest expanding the model to include additional illnesses and investigating CNN and deep learning techniques for possible efficiency gains. For data mining, the authors [15] suggested a model that used the KNN, NB, DT, and RF classification techniques. To extract important information and features from huge datasets, they applied regression, clustering, and association rules of data mining. They found that KNN (k = 7) had the highest accuracy. It is possible to improve the early detection of heart disease by putting more sophisticated models into practice and adding more data mining methods, loke SVM, association rule, time-series analysis, genetic algorithms and clustering criteria.



Author [16] Sonam et al. created heart disease prediction model by using NB and DT classifier. The Naïve Bias classifier doesn't perform better than the Decision Tree classifier. Naïve Bias classifier's performance was enhanced by eliminating unnecessary features from the dataset. The significance of categorization methods and data preparation for precise heart disease prediction is emphasized by this study.

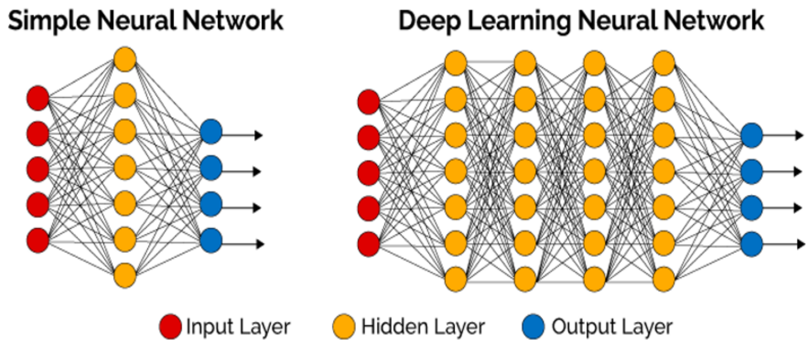
The authors of Ref. [17] suggested a technique for utilizing symptom information to predict CVD. The Cleveland dataset's 14 variables were analyzed using six classification methods; the maximum accuracy of 91.7% was obtained using SVM plus MLP. Performance could be further enhanced by using ensembles and experimenting with additional parameter choices. This approach has the potential to predict diseases accurately and quickly.

3. METHODOLOGY

Model Architectures

Deep Neural Network (DNN):

- A DNN is a type of ANN which has multiple layers between the input and output layers.
- The network can discover patterns thanks from existing data and relationships between data, thanks to these layers. It is suitable for tasks like NLP and Image processing and segmentation.
- DNN, which can stand for Deep Neural Network, is a type of Machine learning algorithm.
- NLP, signal processing, computer vision, and healthcare are just a few of the fields that use DNNs.
- We've all been reading the word "deep" for a while. Let's examine the meaning behind the term "deep neural network." One input layer and one output layer were the foundation of the previous rules created for networks like perceptron's, HNNs, etc.
- If it contains more than three layers, including the input and output layers, it is called a DNN. As a result, deep in its most unadulterated state has multiple hidden layers. Depending on the output of the preceding layer, each node layer in DNNs [9] trains on a distinct set of characteristics. Therefore, the more you penetrate the net, the more you may move forward within it, and the more intricate features the nodes are able to identify [12]. It does this by recombining and learning from the prior layer's features. This is referred to as the future hierarchy. Complex nonlinear relationships are permitted by these nets.
- DNNs' primary benefit is their capacity to handle unstructured and unlabeled data, which makes up the majority of the world's data. The majority of data, particularly in the medical industry, is unlabeled and unstructured. DNNs are therefore suitable for handling this volume of data.

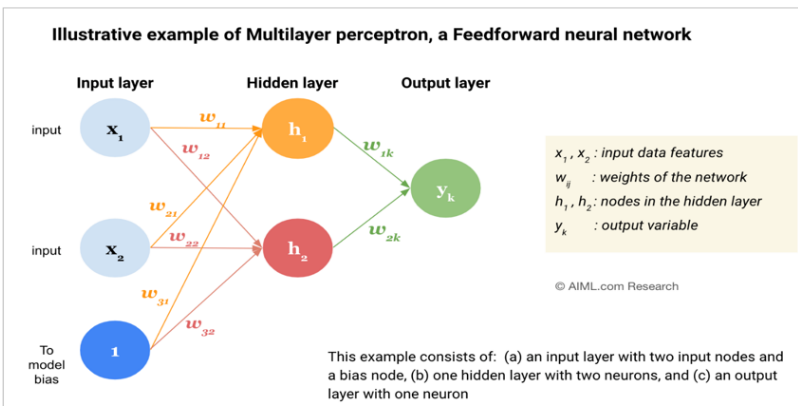


MLP

Dense layers that are fully connected make up a multi-layer perception (MLP), which converts input data between dimensions. It consists of one or more hidden layers, an input layer, and an output layer that's why it is called as multilayer. Modelling complex relationships between inputs and outputs is the goal of an MLP.

Components of Multi-Layer Perceptron (MLP)

- **Input Layer:** Every node or neuron in this layer represents an input characteristic. For example, the input layer will have three neurons if you have three input features.
- **Hidden Layers:** MLP can have an arbitrary number of hidden layers, with an arbitrary number of nodes in each layer. The data from the input layer is processed by these layers.
- **Output Layer:** This layer produces the ultimate forecast or outcome. The output layer will have a similar number of neurons if there are several outputs.



Important features of MLPs include:

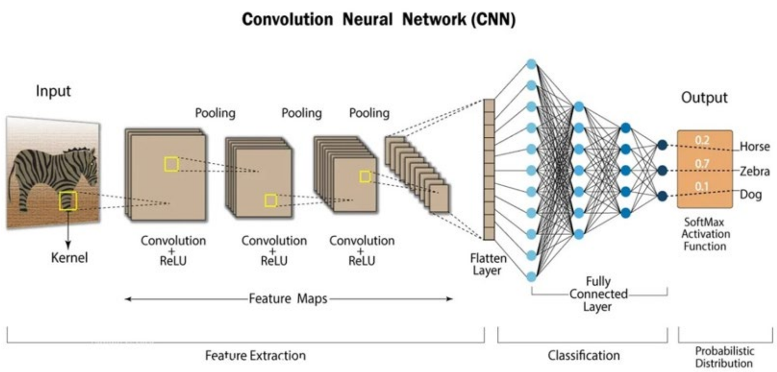
- **Multiple Layers:** MLPs may simulate more intricate data patterns because they include hidden layers, in contrast to single-layer perceptron's.
- **Feedforward Structure:** Data moves from the input layer to the output layer via hidden layers in a single direction.
- **Non-linear Activation Functions:** To introduce non-linearity and allow the network to learn intricate relationships, each neuron in an MLP usually employs a non-linear activation function (such as sigmoid or ReLU).

One kind of deep learning algorithm that works especially well for evaluating visual data, such as pictures and videos, is CNN, also known as a ConvNet. This kind of neural network is quite good at automatically identifying and categorizing patterns in visual data. CNNs are frequently employed for applications including image segmentation, object detection and image recognition.

Here's a more detailed breakdown:

What CNNs do:

- **Feature Extraction:** Using a method known as convolution, CNNs are trained to recognize significant features in images, such as edges, textures, and forms.
- **Pattern Recognition:** They do well on tasks like object recognition, facial recognition, and image classification because they are adept at identifying patterns in visual data.
- **Automatic Feature Learning:** CNNs automatically learn these features from the data itself, in contrast to conventional machine learning models that call for manual feature engineering.



LightGBM

A strong, open-source, and effective machine learning framework for gradient boosting is called LightGBM, or Light Gradient Boosting Machine. Because of its speed and scalability, it can handle big datasets and challenging Machine learning tasks like classification, ranking, regression. LightGBM is a robust, open-source, and effective gradient boosting Machine learning system. Because of its speed and scalability, it can handle big datasets and challenging machine learning tasks like classification, ranking, regression.

By iteratively creating decision trees and aggregating their forecasts, LightGBM uses a gradient boosting technique. In order to produce a deeper and maybe more accurate tree structure, the algorithm focuses on determining each leaf node's optimal split point. It employs methods such as

- **Gradient-based One-Side Sampling (GOSS):** This technique reduces computation time by selecting instances based on their gradients, giving preference to those with bigger gradients.
- **Exclusive Feature Bundling (EFB):**

By merging mutually exclusive features, this method lowers dimensionality and increases efficiency.

Dataset Description

An IEEE Dataport dataset containing 1190 cases relating to heart disease was used in this investigation. Both continuous (cholesterol, age, old peak, max. heart rate, and resting bp) and categorical (st slope, resting ECG, chest pain type) factors are included in the dataset. Additionally, it possesses binary traits like sex, fasting BS, and exercise angina.

Table 1

Data element	Data Element	Explanation
Age	Age	Patient age
Sex	Gender	0 is used for Female, 1 is used for Male,
Cp	Chest pain	Four types of chest pain: 0 = typical angina, 1= atypical angina, 2 = nonanginal pain, and 3 = asymptomatic.
Trestbps	Rest blood pressure	mm/Hg of the patient's resting blood pressure upon hospital admission.
Chol	Cholesterol value	mg/dL is the unit of measurement for blood cholesterol.

Fbs	Blood sugar level during fasting	After an overnight fast, a fasting blood sugar level of greater than 120 mg/dl is deemed high(1- true). On the other hand, it is regarded as being within the normal range if it detects not more than 120 mg/dl (0 - false).
Restecgr	Electrocardiogram outcomes at rest	Three groups can be distinguished by the results of the Resting ECG test: a score of 0 indicates a flat result, a score of 1 indicates the existence of abnormalities in the ST-T waves, and a score of 2 indicates the presence of left ventricular hypertrophy.
Thalach	Highest heart rate achieved	The maximum heart rate recorded during physical activity.
Exang	Angina triggered by exercise	With 0 signifying the absence of angina and 1 signifying its existence, angina onset during exercise is indicated.
Oldpeak	ST depression brought on by exercise versus rest	When the results of an ECG test are compared between those obtained during relaxation and exertion, ST depression is usually seen.
Slope	The peak exercise ST segment's slope	The following categories apply to the maximum slope (ST depression) during exercise testing: One indicates an upward slope, two indicates a flat slope, and three indicates a downhill slope.
Target	Diagnosis of heart disease	Whereas a label of "1" denotes the presence of cardiac disease, a label of "0" denotes its absence.

- **Dataset I:** This dataset comes from the UCI Cleveland Repository and has 12 features and 919 occurrences.
- **Dataset II:** From the IEEE Dataport comprehensive heart disease dataset, this dataset includes 12 multivariate features and 1190 cases.

Data Preprocessing

Data preparation is required since the caliber of the data utilized to build a machine learning model has substantial impact on its performance. Data preparation entails data cleaning by removing missing data points and outliers, transcoding, resampling, and feature selection. We started looking for any missing information, but we couldn't find any. These are some missing variables from the original dataset's properties that could lead to erroneous results and lower the model's accuracy. Predictive models' accuracy and dependability may be hampered by outliers and irrational values in raw datasets. This is particularly crucial for applications like data set analysis for heart disease. The Inter Quartile Range (IQR) method, a reliable statistical approach, was used to overcome this problem (Chung et al. 2014). Our heart disease prediction model's accuracy and dependability are increased by the IQR approach, which makes it possible to identify outliers and deal with them methodically and impartially. Physiological markers for healthy people have levels that fall within a range.

As seen in Table 2, we looked for outliers and found a few.

Table 2 List of Outliers

Attributes	**Outlier Values**
Age	None
Chol	404,407,409,412,417,458,466, 468,491
RestingBP	172,174,178,180,185,190

Hybrid Model Architecture

To analyse data, Several Deep learning as well as Machine learning methods are used.

The suggested CNN, DNN, MLP, and LightGBM models process data in a sequential manner. Initially, by automatically identifying characteristics in the current raw data, Manual feature engineering is no longer necessary thanks to the CNN component. Second, by capturing context and long-term dependencies, the MLP component enables the model to produce more precise classifications or predictions. Lastly, the model is more effective and efficient than separate feature extraction and sequence modelling processes since it can be trained end-to-end utilizing back-propagation over time. This paper suggested a hybrid model in our study to analyse the data.

Our suggested approach presents a hybrid paradigm that makes use of all architectures' advantages. This enables us to efficiently capture temporal and spatial dependencies in the data. Since no prior work has applied this hybrid model to the dataset, our method closes a gap in the literature. We can extract intricate trends and capture long-term dependencies by combining CNN, DNN, MLP, and LightGBM, which produces better results than current techniques.

4. RESULTS AND DISCUSSION

4.1. MODEL EVALUATION

Several classification algorithms, including as CNN, LightGBM, TabNet, catBoost, Transformer DNN, and MLP, were used in our study. The features were processed using feature engineering (FE) techniques, and outliers were identified and eliminated.

Table 3

Performance Metrics for Deep Learning Ensemble and Individual Models in Cardiovascular Disease Prediction

Model	Accuracy	F1 Score	ROC AUC
Deep Learning Ensemble	**0.92**	**0.95**	**0.88**
Transformer DNN	0.85	0.90	0.59
MLP	0.40	0.47	0.45
CNN	0.29	0.00	0.36
TabNet	0.87	0.91	0.86
LightGBM	0.91	0.95	0.95
CatBoost	0.91	0.94	0.94

5. DISCUSSION

From that, it comes to know DNN and MLP is giving poor accuracy. LightGBM is giving 90.94% accuracy while CatBoost is giving 91.07% accuracy. Transformer DNN is performing well compared to TabNet. Transformer DNN is giving 84.76% accuracy while TabNet is giving 86.87% accuracy. If all the algorithms are ensemble together and create ensemble model it gives 91.94% accuracy which is really a good compared to individual model accuracy.

6. CONCLUSION

To sum up, our research significantly advances the use of Deep learning, Machine learning methods for the precise prediction of cardiac disease. We have successfully shown through the examination of combination of Machine learning, Deep learning algorithms that CNN, Transformre DNN, MLP, LightGBM, and CatBoost hybrid model is the most efficient approach, attaining an impressive accuracy of 91.94%. This research shows how sophisticated combined machine learning and deep learning models can be used to predict heart disease (CVD), offering a useful tool for prevention and early pedication. Since age, blood pressure, and cholesterol levels are now recognized as critical indicators of heart disease, we have a better understanding of the factors influencing the development of CVD.

This useful data may help physicians create individualized treatment programs and risk-reduction techniques for patients, which could ultimately result in better clinical outcomes. Using a hybrid model, a varied dataset, and feature engineering techniques, our study effectively fills in several research gaps and constraints. By improvin0067 the Machine learning models efficiency for heart disease prediction, these contributions establish as potentially useful instruments in the field of managing heart disease. We do admit, though, that more investigation is necessary to confirm our results on bigger and more varied datasets. The body of information in the sector will surely grow as Machine learning and Deep learning methods and their applications in heart disease prediction and prevention are further explored. This will also allow health professionals to make more informed decisions.

CONFLICT OF INTERESTS

None.

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None.

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