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A CLINICAL DECISION SUPPORT SYSTEM FOR HEART DISEASE PREDICTION USING DEEP LEARNING

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Abstract - Regrettably, heart disease presently stands as the leading global cause of mortality and its occurrence is on the rise. Detecting early stages of heart disease before a cardiac event presents challenges. Despite the abundance of heart disease data in healthcare settings like clinics and hospitals, this data isn't effectively utilized to uncover concealed patterns. Machine learning offers a solution by transforming medical data into valuable insights, creating decision support systems (DSS) that learn and enhance from past experiences. Deep learning, notably, has garnered attention from both industry and academia. This research's core aim is precise heart disease diagnosis, achieved through a Keras-based deep learning model employing a dense neural network. The model is tested with diverse configurations of hidden layers (3 to 9 layers) with each layer using 100 neurons and the Relu activation function. Numerous heart disease datasets are used for analysis, evaluating individual and ensemble models across all datasets. Utilizing metrics like sensitivity, specificity, accuracy, and f-measure, the dense neural network's performance is gauged. Different layer combinations perform variably due to attribute categories. Through extensive experimentation, the proposed framework's results are examined, revealing that the deep learning model in this work surpasses individual models and alternative ensemble methods in accuracy, sensitivity, and specificity across all heart disease datasets.

Keywords:- *Heart disease, Machine learning, Deep learning, Keras, Dense neural network, Diagnosis, Decision support system (DSS), Sensitivity, Specificity, Ensemble methods.*

I. INTRODUCTION

Heart disease, also referred to as cardiovascular illness, has become the primary cause of death worldwide and is becoming increasingly common. There are numerous symptoms associated with heart disease such as chest pain, sweating and fatigue, whereas mostly people feel nothing until a heart attack occurs.To diagnose heart disease in patients, medical professionals use various techniques such as performing physical examinations, analyzing the patient's medical history, and conducting several medical tests. Normally a suspected heart disease patient is evaluated by using the clinical history, chest x-ray and physical examination, in spite of the fact that often some signs and isolated symptoms do not match up with these objective methods. Most of the people having heart attacks and heart strokes have not been identified as ‘‘at risk’’ by the medical experts and medical specialist. About 1/3rd of the patients have been misdiagnosed by medical specialists. There are many symptoms of heart disease common to many other disease such as fatigue and chest pain which makes it difficult to diagnose at early stages. In addition, detecting heart disease has become a difficult task for many healthcare providers. This is because many patients do not show any symptoms until they suffer a sudden cardiac arrest.

The detection and prevention of cardiovascular diseases (CVDs) have become critical global health concerns, with heart disease being a leading cause of mortality worldwide [2]. To address this, researchers have explored various methodologies, including the application of deep neural networks (DNNs) for heart disease detection [1]. This emerging field leverages advanced computational techniques to enhance diagnostic accuracy and prognosis. Epidemiological data from sources such as the World Health Organization [2] and Worldlifeexpectancy [3] highlight the significance of understanding and predicting heart diseases on a global scale. Analytical studies, like the one conducted by Sowmiya and Sumitra [4], and comparative analyses by researchers such as Hasan [7], have explored classification techniques and machine learning algorithms to predict heart diseases, providing valuable insights into effective diagnostic strategies. The integration of data mining techniques has further enriched the diagnostic landscape. Kumar et al. [5] performed a comparative analysis of data mining techniques, specifically for diabetic patients with heart disease, shedding light on personalized approaches to disease prediction. Additionally, knowledge-based clinical decision support systems, as discussed by Bashir et al. [9], have shown promise in improving cardiovascular disease prediction through intelligent ensemble voting schemes. In this context, advancements in feature selection [12], dimensionality reduction techniques like auto-encoders [15], and the exploration of clustering algorithms [14] have contributed to refining the precision and efficiency of heart disease prediction models. The interdisciplinary nature of these studies emphasizes the integration of computational methodologies and medical expertise for optimal clinical decision support [13]. As researchers continue to innovate in this domain, the development of robust and accurate predictive models holds significant promise for early detection and effective management of heart diseases on a global scale.

II. LITERATURE SURVEY

The literature on heart disease detection and prediction encompasses a variety of approaches ranging from traditional statistical methods to advanced machine learning techniques. N.-S. Tomov and S. Tomov [1] explored the application of deep neural networks for heart disease detection. This aligns with the global concern highlighted by the World Health Organization (WHO) [2], which reports cardiovascular diseases (CVDs) as a leading cause of mortality worldwide. Disparities in the prevalence of coronary heart disease across countries were documented by Worldlifeexpectancy [3]. Several studies have investigated the use of classification techniques for heart disease diagnosis. C. Sowmiya and P. Sumitra [4] conducted an analytical study, while A. Kumar et al. [5] performed a comparative analysis of data mining techniques, particularly focusing on diabetic patients.

The importance of community-based interventions was demonstrated by Y.-J. Huang et al. [6], who examined a nurse-led education and coaching initiative for coronary heart disease high-risk individuals in China. Machine learning algorithms have gained prominence in heart disease prediction. R. Hasan [7] conducted a comparative analysis of various machine learning algorithms, emphasizing their potential for accurate predictions. S. Khan and S. T. Rasool [8] discussed the current use of cardiac biomarkers in different heart conditions, providing insights into the evolving diagnostic landscape. Clinical decision support systems have been proposed as a valuable tool in improving cardiovascular disease prediction.

S. Bashir et al. [9] introduced a knowledge-based clinical decision support system utilizing an intelligent ensemble voting scheme, while V. Vives-Boix et al. [11] developed a system for monitoring chronic patients. Feature selection approaches have also been explored to enhance heart disease prediction models. S. Bashir et al. [12] highlighted the importance of feature selection in improving prediction accuracy. Moreover, dimensionality reduction techniques, such as auto-encoders, have been investigated in the context of heart disease prediction [15].

In conclusion, the literature survey reveals a diverse range of methodologies applied to heart disease detection and prediction, spanning from traditional statistical methods to sophisticated machine learning approaches and clinical decision support systems. The studies emphasize the global significance of addressing cardiovascular diseases and the potential for advanced technologies to contribute to more accurate and efficient diagnostic processes.

III. METHODOLOGY

Modules:

- Data exploration: using this module we will load data into system
- Image processing: Using the module we will process of transforming an image into a digital form and performing certain operations to get some useful information from it.
- Model generation: Building the model -KNN -LinearSVC -Gaussian Process -Decision Tree -Naive Bayes -QDA -AdaBoost -Bagging -Boosting -Stacking Classifier(RF + MLP with LightGBM) -Voting Classifier (DT + RF) -DNN.
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

A) System Architecture

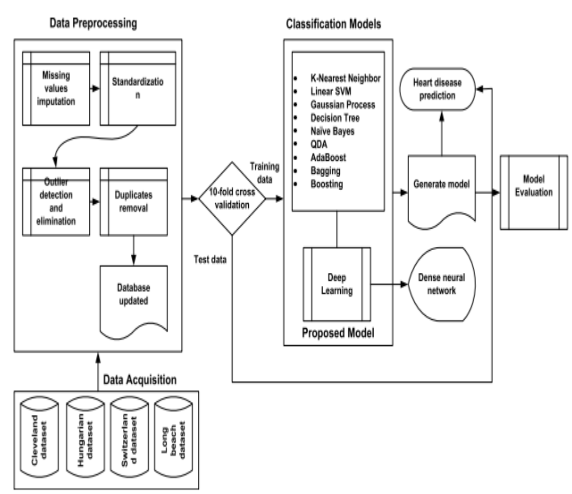

Fig 1: System Architecture

Proposed work

We proposes the development of a decision support system(DSS) for the precise diagnosis of heart illness using deep learning techniques. Our proposed approach uses a Keras-based deep learning model with a dense neural network to diagnose heart disease. The model is tested with various configurations of hidden layers in the dense neural network, ranging from 3 layers to 9 layers, with each layer using 100 neurons and the Relu activation function. Numerous heart disease datasets are used for analysis, evaluating individual and ensemble models across all datasets. Utilizing metrics like sensitivity, specificity, accuracy, and f-measure, the dense neural network's performance is gauged. Different layer combinations perform variably due to attribute categories.

B) Dataset Collection

This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to date. The "goal" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4. Experiments with the Cleveland database have concentrated on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).

The names and social security numbers of the patients were recently removed from the database, replaced with dummy values.

One file has been "processed", that one containing the Cleveland database. All four unprocessed files also exist in this directory.

To see Test Costs (donated by Peter Turney), please see the folder "Costs"

Variable Name	Role	Type	Demographic	Description	Units	Missing Values
age	Feature	Integer	Age		years	no
sex	Feature	Categorical	Sex			no
cp	Feature	Categorical				no
trestbps	Feature	Integer		resting blood pressure (on admission to the hospital)	mm Hg	no
chol	Feature	Integer		serum cholestoral	mg/dl	no
fbs	Feature	Categorical		fasting blood sugar > 120 mg/dl		no
restecg	Feature	Categorical				no
thalach	Feature	Integer		maximum heart rate achieved		no
exang	Feature	Categorical		exercise induced angina		no
oldpeak	Feature	Integer		ST depression induced by exercise relative to rest		no

Fig 2: Dataset

C) Pre-processing

Data preprocessing for the Heart Disease dataset involves loading the data from different sources (Cleveland, Hungarian, Switzerland, Long Beach VA) into the system. Using pandas and Keras dataframes, irrelevant columns are removed to streamline the dataset. Visualization tools like seaborn and matplotlib aid in exploring the data. Label encoding is applied to convert categorical variables into a numerical format. Feature selection techniques are then employed to identify the most significant features. Subsequently, the data is divided into training and testing sets for both deep learning and machine learning models. The process includes building various models, such as KNN, LinearSVC, Gaussian Process, Decision Tree, Naive Bayes, QDA, AdaBoost, Bagging, Boosting, Stacking Classifier, Voting Classifier, and Deep Neural Networks with different hidden layers. The extension involves implementing ensemble methods like Voting Classifier and Stacking Classifier, resulting in improved accuracy. Ultimately, the Flask framework with SQLite is used for user signup and login, and the trained models are utilized for predictions, with the results displayed through the front end.

D) **Training & Testing**

In the training phase, the dataset is explored and preprocessed using pandas and Keras dataframes. Visualization is performed using seaborn and matplotlib, followed by label encoding and feature selection. The data is then split into training and testing sets for both machine learning and deep learning models. Various machine learning models such as KNN, LinearSVC, Gaussian Process, Decision Tree, Naive Bayes, QDA, AdaBoost, Bagging, Boosting, and ensemble methods like Stacking Classifier and Voting Classifier are built for multiple heart disease datasets, each with different configurations of hidden layers in deep neural networks (DNN). The models are trained using the training sets.

In the testing phase, the Flask framework with SQLite is utilized for user signup and login. Users provide input features for prediction, which undergo preprocessing. The pre-trained models are then employed to predict the outcomes. The final results are displayed through the frontend, providing an accurate and robust prediction for heart disease. The ensemble techniques, specifically Stacking Classifier and Voting Classifier, exhibit superior accuracy, surpassing 93%. The incorporation of user authentication and a user-friendly front end further enhances the application for user testing.

E) Algorithms.

KNN –K-Nearest Neighbors Algorithm. The k-nearest neighbors algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.

LinearSVC –Linear Support Vector Machine (Linear SVC) is an algorithm that attempts to find a hyperplane to maximize the distance between classified samples.

Gaussian Process –The Gaussian Processes Classifier is a classification machine learning algorithm. Gaussian Processes are a generalization of the Gaussian probability distribution and can be used as the basis for sophisticated non-parametric machine learning algorithms for classification and regression.

Decision Tree –Decision Tree algorithm belongs to the family of supervised learning algorithms. Unlike other supervised learning algorithms, the decision tree algorithm can be used for solving regression and classification problems too.

Naive Bayes –It is a classification technique based on Bayes' Theorem with an independence assumption among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

QDA –Quadratic Discriminant Analysis (QDA) is a generative model. QDA assumes that each class follow a Gaussian distribution. The class-specific prior is simply the proportion of data points that belong to the class. The class-specific mean vector is the average of the input variables that belong to the class.

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AdaBoost –AdaBoost algorithm, short for Adaptive Boosting, is a Boosting technique used as an Ensemble Method in Machine Learning. It is called Adaptive Boosting as the weights are re-assigned to each instance, with higher weights assigned to incorrectly classified instances.

Bagging –Bagging, also known as bootstrap aggregation, is the ensemble learning method that is commonly used to reduce variance within a noisy dataset. In bagging, a random sample of data in a training set is selected with replacement—meaning that the individual data points can be chosen more than once.

Boosting –The boosting algorithm assigns equal weight to each data sample. It feeds the data to the first machine model, called the base algorithm. The base algorithm makes predictions for each data sample.

Stacking Classifier(RF + MLP with LightGBM) – A stacking classifier is an ensemble learning method that combines multiple classification models to create one "super" model. This can often lead to improved performance, since the combined model can learn from the strengths of each individual model.

Voting Classifier (DT + RF) –DNN - A Voting Classifier is a machine learning model that trains on an ensemble of numerous models and predicts an output (class) based on their highest probability of chosen class as the output.

IV. EXPERIMENTAL RESULTS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

Accuracy: A test's accuracy is defined as its ability to recognize debilitated and solid examples precisely. To quantify a test's exactness, we should register the negligible part of genuine positive and genuine adverse outcomes in completely examined cases. This might be communicated numerically as:

Accuracy = TP + TN TP + TN + FP + FN.

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

Precision: Precision measures the proportion of properly categorized occurrences or samples among the positives. As a result, the accuracy may be calculated using the following formula:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a machine learning metric that surveys a model's capacity to recognize all pertinent examples of a particular class. It is the proportion of appropriately anticipated positive perceptions to add up to real up-sides, which gives data about a model's capacity to catch instances of a specific class.

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

F1-Score: The F1 score is a machine learning evaluation measurement that evaluates the precision of a model. It consolidates a model's precision and review scores. The precision measurement computes how often a model anticipated accurately over the full dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

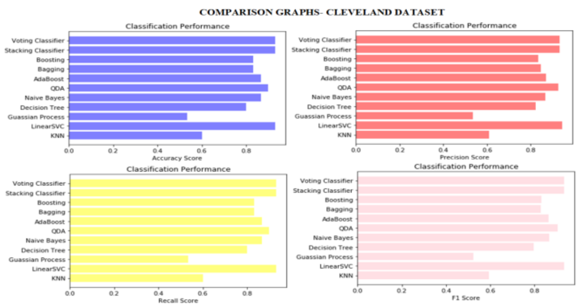

Fig 3: Comparison of All Algorithms with Cleveland Dataset

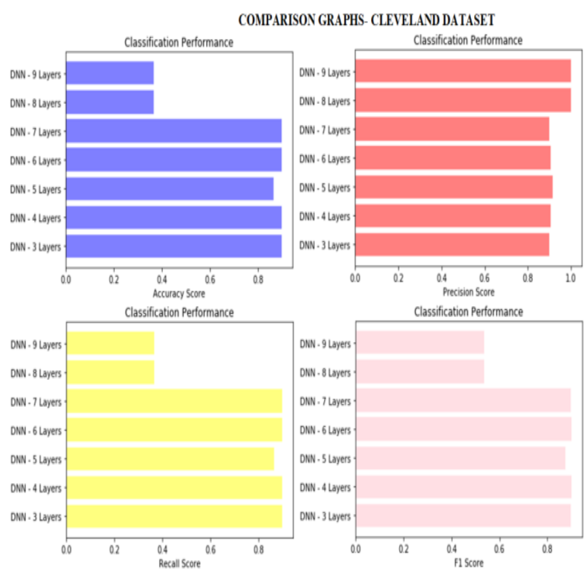

Fig 4: Comparison of DNN Layers with Cleveland Dataset

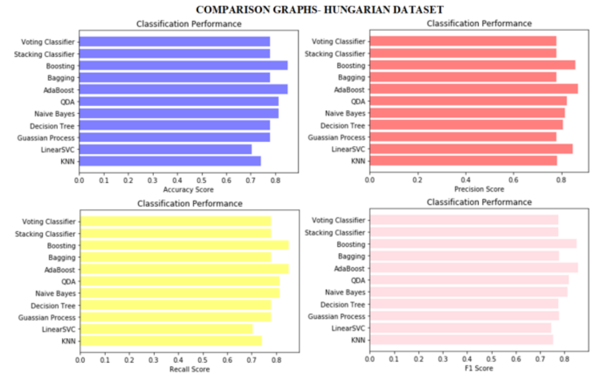

Fig 5: Comparison of All Algorithms with Hungarian Dataset

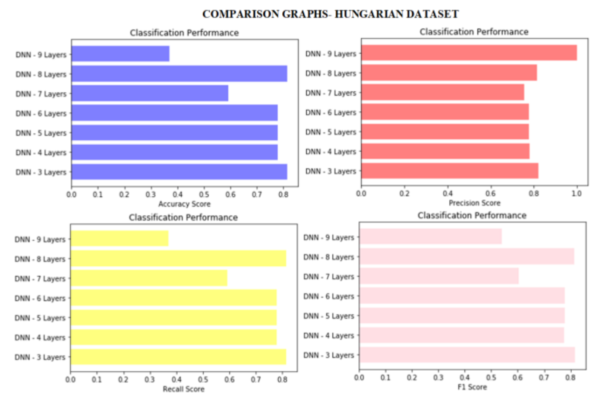

Fig 6: Comparison of DNN layers with Hungarian Dataset

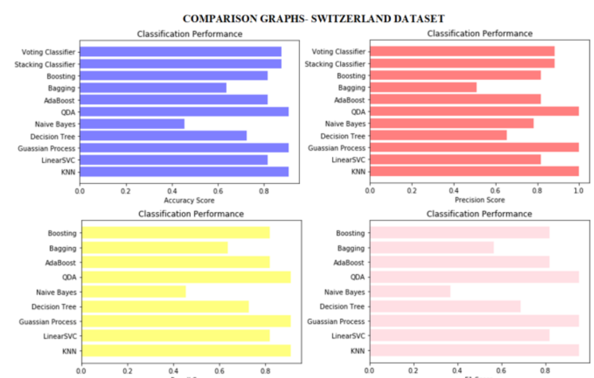

Fig 7: Comparison of All Algorithms with Switzerland Dataset

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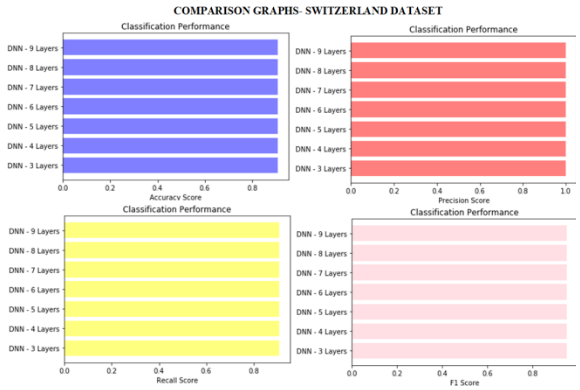

Fig 8: Comparison of DNN layers with Switzerland Dataset

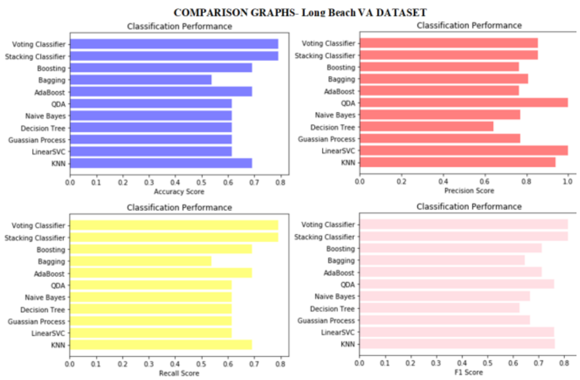

Fig 9: Comparison of All Algorithms with Long Brach VA Dataset

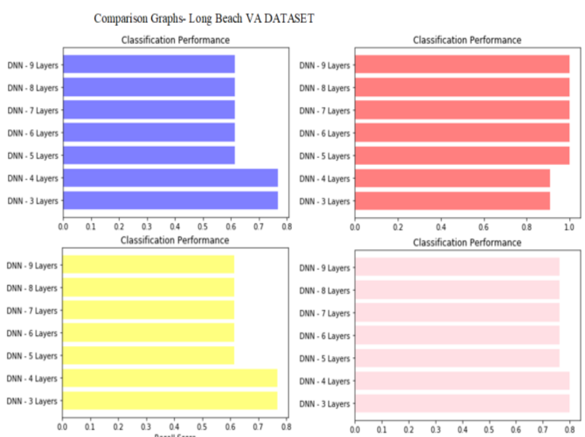

Fig 10: Comparison of DNN Layers with Long Brach VA Dataset

B) Frontend

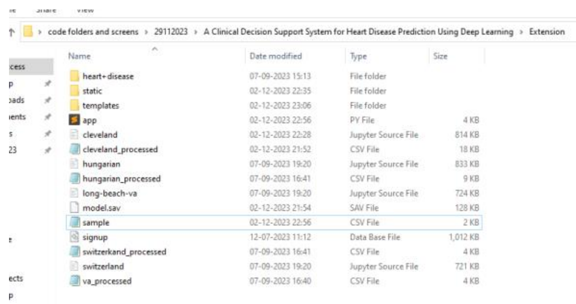

Fig 11: Code file

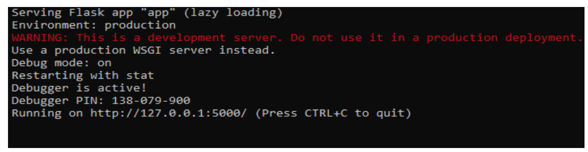

Fig 12: URL Link of web page

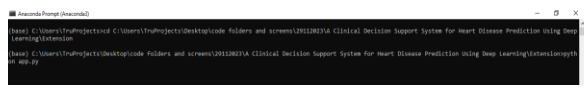

Fig 13: Path of code file

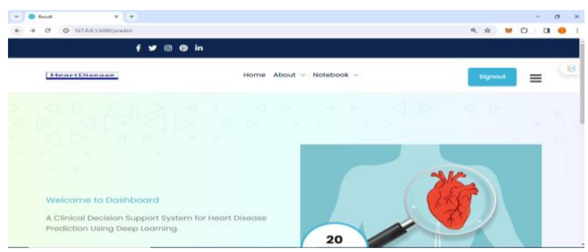

Fig 14: Home Page

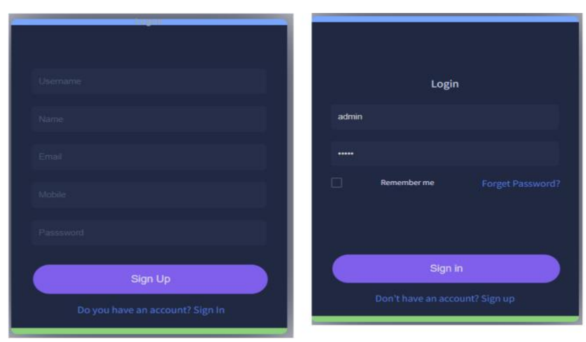

Fig 13: User Sign Up & Login Pages

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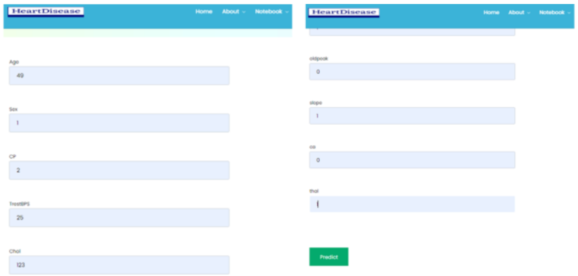

Fig 14: Enter data for testing

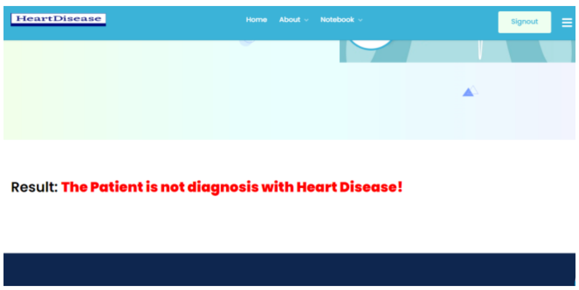

Fig 15: Result: Patient is not diagnosis with Heart Disease

V. CONCLUSION

Utilizing deep learning proves to be an effective and precise method for diagnosing and predicting heart disease. The proposed model outperformed other techniques significantly in terms of accuracy, sensitivity, and specificity. In future, we aim to enhance this approach by incorporating imagery data from individuals with heart conditions. These images will be acquired through laboratory tests and medical imaging procedures. Furthermore, the application of Convolutional Neural Network (CNN) on this imagery data will enable the accurate diagnosis of heart diseases. A notable advantage of employing CNN on the provided imagery data is its automatic detection of crucial features. Moreover, additional performance metrics like the confusion matrix, PR curve, and ROC curve will be employed for model assessment. Additionally, subjecting the CNN model to combined structured and unstructured data can potentially amplify the prowess and accuracy of CNN algorithms in predicting heart disease.

VI. FUTURE SCOPE

The future scope involves advancing the proposed deep learning model by integrating imagery data from individuals with heart conditions, obtained through laboratory tests and medical imaging. The incorporation of Convolutional Neural Network (CNN) on this imagery data promises enhanced diagnostic accuracy, benefiting from automatic detection of crucial features. Extending evaluation metrics to include the confusion matrix, PR curve, and ROC curve will provide a comprehensive model assessment. Furthermore, synergizing CNN with combined structured and unstructured data holds the potential to amplify predictive accuracy in diagnosing heart diseases, paving the way for a robust and comprehensive approach to cardiovascular health assessment.

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