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Heart Disease Prediction Using Novel Ensemble and Blending Based Cardiovascular Disease Detection Networks: EnsCVDD-Net and BlCVDD-Net

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Abstract: “Cardiovascular diseases (CVDs)” are one of the most common causes of death around the world, so it's important to get correct and quick diagnoses to lower the risks. This study uses advanced “Deep learning (DL) and machine learning (ML)” methods to make diagnoses more accurate. traditional ML methods rely largely on manual feature engineering, but DL methods are great at automatically extracting features, which makes them perfect for working with complicated datasets. This paper uses the heart ailment Dataset to deal with class imbalance through “Adaptive synthetic (Adasyn)” Oversampling and suggests a new ensemble-based detection approach. comprehensive tests show that the voting Classifier is better than any one model, “with an accuracy of 91.7%, a precision of 92.0%, a recall of 91.7%, and an F1-score of 91.8%”. these results show how well ensemble methods can work with different types of data and get excellent diagnostic accuracy. This shows how these methods could help improve CVD diagnosis.

“Index Terms - *Cardiovascular disease detection, deep learning, heart disease, LeNet, gated recurrent unit, multilayer perceptron”.*

1. INTRODUCTION

“Cardiovascular diseases (CVDs)” are one of the top causes of death in the world, making them a serious global health problem [1]. these disorders include many different problems with the heart and blood vessels that stop blood from flowing normally through the body. The heart is one of the most important organs, and it needs to work well for life. If it doesn't work right because of disease, it can have serious effects, such as death or long-term impairments [2]. In the past few decades, cases of CVDs have soared and afflict millions of individuals internationally. the “world health organization (WHO) says that heart disease is responsible for 32% of all deaths, with 85% of these” deaths caused by heart attacks and strokes. This demonstrates the need of diagnosing and treating heart disease at its early stages [1]. The expanding number of CVDs is putting a lot of stress on healthcare systems around the world, which need more money to diagnose, treat, and manage them [3].

CVDs can be caused by many risk factors, some of which include bad lifestyle habits like poor eating, failure to exercise, obesity, smoking and drinking too much alcohol [4]. These factors are known to lead to high blood pressure, high levels of cholesterol and insulin resistance, conditions that greatly increase your risk of contracting heart disease. The problem with late diagnosis of CVDs is that the patient is usually forced to undergo invasive procedures like angiography or bypass surgery, which is not only painful, but also strains healthcare systems to spend more money on treatment. It is highly crucial to diagnose many disorders in the early stage to prevent the development of continuous worsening. This is making it possible to commence treating such as with drugs, lifestyle changes, and counseling immediately. however, it remains difficult to precisely predict the occurrence of heart disease due to the complex relationships between factors such as high blood pressure, family background, cholesterol levels, and diabetes. It is difficult in this way to detect early symptoms of the disease in the presence of the healthcare workers [5].

2. RELATED WORK

Due to the increasing prevalence of complications related to the heart and the fact that such problems have a huge impact on the world mortality rate, the identification of the problem of cardiovascular diseases (CVDs) at an early age is one of the priority areas now. “Machine learning (ML) and deep learning (DL)” models have been used by researchers to enhance speed and accuracy in the detection of cardiac diseases. these algorithms have also proven to be quite promising in their efforts to process large amounts of data and identify otherwise overlooked patterns that old medical practices could not help identify. in order to enhance the accuracy of their predictions, most of these studies employ a combination of algorithms, like ensemble learning, sequential feature selection, and hybrid models.

Hymavathi et al. [6] developed such an ensemble meta-feature integration strategy based on the use of multiple ML models to predict the disease of the heart more accurately. This is because the model has multiple perspectives of the data through combination of meta-features that makes it more robust and quicker than the conventional procedures. The authors illustrate how ML approaches can be valuable, in particular when applied to healthcare data, be it noisy and imbalanced. Differences in data are easier to address with the ensemble method making the prediction of heart disease locations more accurate.

The application of supervised learning and stochastic gradient boosting to predict cardiac disease was also investigated by Jawalkar et al. [7]. This paper indicates that supervised learning algorithms are able to utilize structured healthcare data through utilization of such techniques as gradient boosting, which is incredible at discovering complex patterns within large datasets. they achieved impressive results when they applied this tactic to predict heart disease providing good evidence of how effective stochastic gradient boosting can be in reducing bias and improving the modus operandi of the model. The model is able to handle various health measures and indicators including the cholesterol levels, age and blood pressure hence, a good possibility of detecting the heart disease in its early-onset.

Chaurasia and Chaurasia [8] have developed a new ensemble method, which is feature selection based to increase the accuracy of the prediction of heart disease as regards applying it in diagnosing the heart disease. The sequential feature choice employed by their solution retains the important aspects of the data albeit simplifying its use. The approach ensures that the model does not receive an excessive amount of irrelevant data that may lead to model overfitting and, as a result, the decrease in the model accuracy. The researchers applied the sequential feature selection approach and the ensemble approaches to creating a powerful prediction model. This demonstrates the significance of feature engineering in healthcare data with high dimensionality where it tends to be challenging to analyze.

Dileep et al. [9] came up with an automatic model of predicting cardiac disease using “cluster-based bi-directional long short-term memory (C-BiLSTM) algorithm. Frequently”, LSTM networks tend to work with time-series data where the sequence of the data occurrence is extremely crucial. By including clustering to the LSTM design, the authors could make the model even more accurate in predicting heart disease. C-BiLSTM algorithm was capable of identifying long-term and short-term relationships in the health data, and this is why forecasts were more accurate. This approach demonstrated the effectiveness of DL models and LSTM networks in particular, when large datasets containing some sequential and temporal data are to be processed.

A combination of CNN and LSTM networks was applied to make predictions about cardiac disease by the works of Sudha and Kumar [10]. They modified the term "Convolutional Neural Networks (CNNs)" which is normally applied in image processing in a manner that it was able to accommodate medical datasets. They combined CNNs and LSTMs to extract features and process sequential data, respectively, to produce the best out of each algorithm. The hybrid CNN-LSTM machine worked better than any general machine learning models, since hybrid CNN-LSTM machine was able to detect both short-term trends in the dataset (via CNN) and long-term dependencies (via LSTM). This combined method did a great deal of predicting on the heart disease by learning high degree characteristics of the health information as well as time correlations in health information.

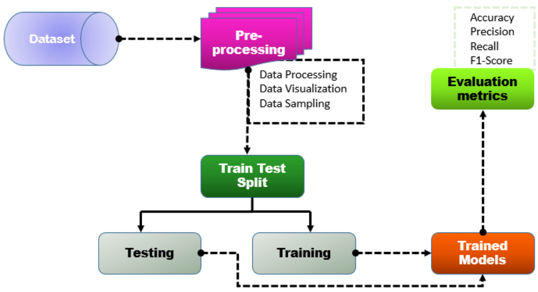
Another contribution was proposed by Sharma et al. [11] who proposed a hybrid deep neural network model that was enhanced using randomized search pass-validation to predict coronary heart disease. The model employed multiple-layer neural networks and employed cross-validation tools to optimize hyperparameters resulting in the model being more accurate on making predictions. By conducting move-validation, the authors managed to ensure that the model was effective in drawing new data. this is very important for real-world use. This hybrid model also shows how powerful neural networks, especially deep neural networks, can be for forecasting complicated health situations where the interactions between variables are often nonlinear and quite complex.

Ogundepo and Yahya [12] did a full performance investigation of a number of supervised classification models that could be used to predict cardiac disease. The study looked at a number of models, such as choice trees, random forests, support vector machines, and logistic regression, to see how well they could predict heart disease based on different health indices. Their results showed that ensemble models, like random forests, always did better than single classifier models. This shows how powerful it is to combine different models to get superior predictions. This study shows how important it is to choose the right machine learning algorithms for predicting heart disease. The data is so complex that it's important to think about the pros and disadvantages of different methods.

those results demonstrate that ML and DL are becoming more and more important in healthcare, especially for finding heart problems. Combining LSTM networks, hybrid models, and ensemble methods made predictions better. these algorithms find subtle patterns in complex, high-dimensional data so that diagnoses can be made quickly and accurately. advanced algorithms, databases, and real-time analytics will help doctors better forecast heart illness so that they can provide better care.

3. MATERIALS AND METHODS

The cautioned approach is all about building a strong foundation for accurately finding “cardiovascular illnesses (CVDs) utilizing machine learning (ML) and Deep learning (DL) methods”. This system uses a wide range of algorithms, such as “LeNet[19], GRU[18], EnsCVDDNet, BICVDD-net, LSTM[18], BiLSTM, CNN+LSTM[15], AdaBoost, KNN[16], SVM[17], XGBoost[20], Naive Bayes[17], Logistic Regression[18], decision Tree[8], and voting Classifier, to effectively” analyze complex clinical data. We use the heart disease Dataset with [14] “Adaptive synthetic (Adasyn)” Oversampling to fix the class imbalance and make the model training better. This method tries to increase the accuracy of handling huge and complex datasets by using DL's ability to automatically extract features and ML models' ability to make predictions. The ensemble-based models, especially EnsCVDDNet and BICVDD-net, are made to use the best parts of each algorithm to make a complete and efficient way to find and diagnose cardiac disease.



“Fig.1 Proposed Architecture”

figure 1 shows a typical workflow for machine learning. It starts with a dataset, which is then cleaned and prepared for analysis. data processing, visualization, and sampling are all possible parts of this pre-processing step. next, the data is separated into two sets: one for training and one for testing. You utilize the training set to create and teach ML models. After being trained, the models are tested on the testing set to see how well they work using measures “like accuracy, precision, recall, and F1-score”. those evaluation measures show how well the model can make correct predictions and sort data.

i) Dataset Collection:

The Behavioral risk factor Surveillance system (BRFSS) 2015's "heart disease health indicators Dataset," which turned into given to us by the centers for disease “control and Prevention (CDC)” [13], is the dataset used in this study. This large dataset has health records for more than 253,680 people and has 22 features, including "HeartDiseaseorAttack," "HighBP," "HighChol," "CholCheck," "BMI," "Smoker," "Stroke," "Diabetes," "PhysActivity," "fruits," "veggies," "HvyAlcoholConsump," "AnyHealthcare," "NoDocbcCost," "GenHlth," "MentHlth," "PhysHlth," "DiffWalk," "sex," "Age," "education," and "income." It contains valuable data towards classification of binary cardiac diseases and is a valuable asset to health related research.

	HeartDiseaseorAttack	HighBP	HighChol	CholCheck	BMI	Smoker	Stroke	Diabetes	PhysActivity	Fruits
0	0.0	1.0	1.0	1.0	40.0	1.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	25.0	1.0	0.0	0.0	1.0	0.0
2	0.0	1.0	1.0	1.0	28.0	0.0	0.0	0.0	0.0	1.0
3	0.0	1.0	0.0	1.0	27.0	0.0	0.0	0.0	1.0	1.0
4	0.0	1.0	1.0	1.0	24.0	0.0	0.0	0.0	1.0	1.0

5 rows × 22 columns

“Fig.2 Dataset Collection Table – Heart Disease” Data”

ii) Pre-Processing:

Another step which should be of interest is data pre-processing as part of preparing the dataset to be analysed. It implies preparing the dataset to train the model by cleaning it out with missing values, duplicates, and irrelevant features. This ensures accuracy and reliability of the outcomes.

a) Data Processing: the beginning of data processing is where one would search out the nulls and eliminate them so as to ensure that the data set remains valid. secondly, one would search out the duplicates, eliminate them, and in this way reduces the number of data that are the same. The dataset indexes are reinitialized to make things consistent following the deletion of redundancies. finally, category columns are scanned to identify the features that require encoding or modification in a way that she or he allows them to interface with the model.

b) Data Visualization: Data visualization is the process of creating graphs of a data set to search patterns, trends and correlation. Histograms, bar charts, and scatter diagrams are used to investigate how such attributes as "Age" and "BMI" and "HeartDiseaseorAttack" are distributed. This will enable us to know the way the data are arranged and establish the most crucial elements leading to heart disease.

c) Data Sampling: The traditional oversampling method is through Adasyn oversampling to overcome the class imbalance in the dataset. This synthesizes data points of the minority category. The approach also ensures that each of the two classes is equally represented and thus enhances the performance of the model by avoiding overfit and allows it to be more general.

iii) Training & Testing:

There are two sets of data: a training set and a testing set. "The training set is 80% of the total and the testing set is 20%. this implies that 80% of" the data is used to train the model so it can learn patterns and make predictions. the other 20% is set aside for testing, which checks how well the model works on data it hasn't seen before. This split makes sure that the model gets trained on a lot of data while still being tested on a separate set of data that doesn't have any bias. This makes the trained model more generic and strong.

iv) Algorithms:

[19] LeNet is a "convolutional neural network (CNN)" that is made to do image processing and feature extraction. it is used to look at organized patterns in data, which makes it good at finding complex features in medical imaging or tabular data format for finding cardiovascular disease.

A **gated recurrent unit (GRU) [18]** is a type of recurrent neural network (RNN) that seeks temporal patterns that occur in some specified order. it is applied to analyse the history or time series of changes in patient health data, and learns more quickly and with less computational complexity than most RNNs.

EnsCVDDNet combines a number of DL networks to enable better predictions. It takes the good of most models, and aims to learn complex patterns using data sets of high dimensions in heart or cardiovascular problems to discover diseases more precisely.

BICVDD-net borrows a combination of the classifiers and DL architectures to give predictions that account the context. it is designed to extract and examine complex relationships in cardiovascular data that ensures the accuracy of categorization and robustness of decisions.

LSTM networks are useful at working with long term dependency data sequences. [18] they are employed to identify certain time trends in the health information of the patients, which is effective in predicting the cardiovascular risks.

BiLSTM (Bidirectional LSTM) works by taking into consideration mixed trends and situational trends in the data of patients through analysis of data in both directions, thus enabling it to understand the context in a better way. When used to analyse changing and situational trends of patient data, it becomes easier to detect the signs of cardiovascular disease.

To gain spatial features and analyse the sequences, CNN+LSTM framework employs convolutional layers to extract spatial features and LSTM layers to extract sequence features [15]. The given mixed method applies equally to such data that have both spatial and temporal characteristics such as sensor outputs or patient health data by numerous sources.

AdaBoost (Adaptive Boosting) is a method that works by combining weak learners repeatedly to make classification better. it is used to make forecasts more accurate and improve the model's overall performance, making sure that all types of cardiovascular data are treated fairly.

KNN (k-Nearest neighbors) sorts data points depending on how close they are to labeled samples. [16] it is used to provide easy, easy-to-understand predictions in datasets with clear clusters, giving us data about trends in cardiovascular health.

Support Vector machine (SVM) builds hyperplanes to sort data into groups. it works well for both binary and multi-class classification, such as looking at cardiovascular data to tell the difference among healthy and at-risk people [17].

XGBoost [20] (extreme Gradient Boosting) is a more advanced ensemble learning technique that makes decision trees one at a time. it is used because it is fast and accurate in working with organized health data and finding important factors that affect heart health.

Naive Bayes looks at how features are related to each other using probability-based classification [17]. it is used on cardiovascular datasets to provide quick and accurate predictions, especially when the features are categorical or independent.

Logistic Regression uses input information to model the likelihood of categorical outcomes. it is used to bet binary outcomes, [18] such whether or not someone has cardiovascular disease, depending on important risk variables.

Decision Tree [8] makes predictions by splitting features and putting them in a hierarchical structure. it is used to classify cardiovascular data in a way that makes sense and is easy to understand, as well as to find important contributing elements.

Voting Classifier combines predictions from several models to make them more accurate and reliable. it is used to combine the best parts of different algorithms to improve the identification of cardiovascular disease.

4. RESULTS & DISCUSSION

Accuracy: A test's accuracy is how well it can tell the difference between sick and healthy people. we can figure out how accurate a test is by looking at the percentage of true positives and true negatives in all the cases that were tested. In math, this can be said as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (1)$$

Precision: Precision looks at the percentage of accurately categorized cases or samples that were labeled as positives. So, the formula for figuring out the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \quad (2)$$

Recall: In ML, recall is a measure of how well a model can find all the relevant examples of a certain class. it is the number of accurately predicted positive observations divided by the total number of real positives. This tells you how well a model captures instances of a certain class.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (3)$$

F1-Score: F1 score is a way to check how accurate a ML model is. It puts together the precision and recall scores of a model. The accuracy statistic counts how many times a model produced a valid prediction on the whole dataset.

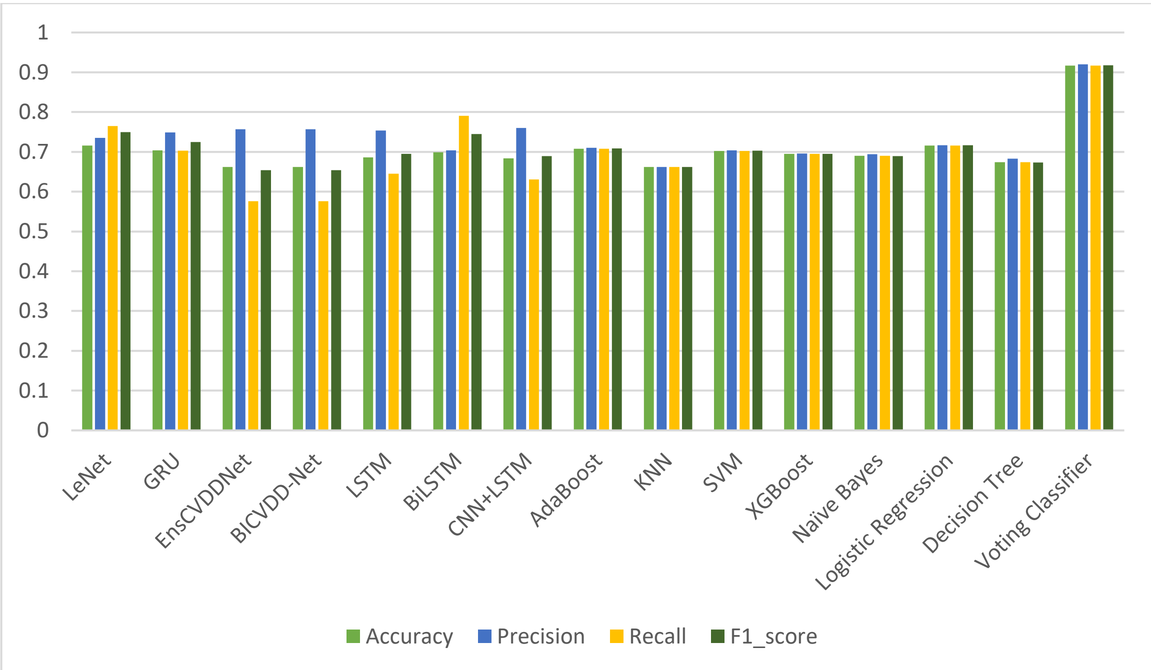
$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(1)$$

We look at the "accuracy, precision, recall, and F1-score" for each algorithm in table 1 to see how well they work. The voting classifier gets the best scores. The table below also shows the metrics of various algorithms for comparison.

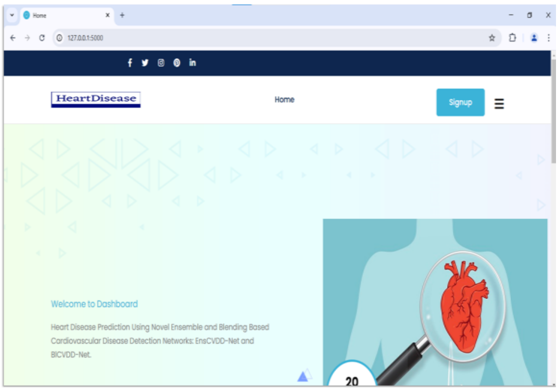
"Table.1 Performance Evaluation Metrics"

ML Model	Accuracy	Precision	Recall	F1_score
LeNet	0.716	0.735	0.765	0.750
GRU	0.704	0.749	0.703	0.725
EnsCVDDNet	0.662	0.757	0.576	0.654
BICVDD-Net	0.662	0.757	0.576	0.654
LSTM	0.686	0.754	0.645	0.695
BiLSTM	0.699	0.704	0.791	0.745
CNN+LSTM	0.684	0.760	0.631	0.689
AdaBoost	0.708	0.710	0.708	0.709
KNN	0.662	0.662	0.662	0.662
SVM	0.702	0.704	0.702	0.703
XGBoost	0.695	0.696	0.695	0.695
Naïve Bayes	0.690	0.694	0.690	0.689
Logistic Regression	0.716	0.717	0.716	0.717
Decision Tree	0.674	0.683	0.674	0.673
Voting Classifier	**0.917**	**0.920**	**0.917**	**0.918**

"Graph.1 Comparison Graphs"

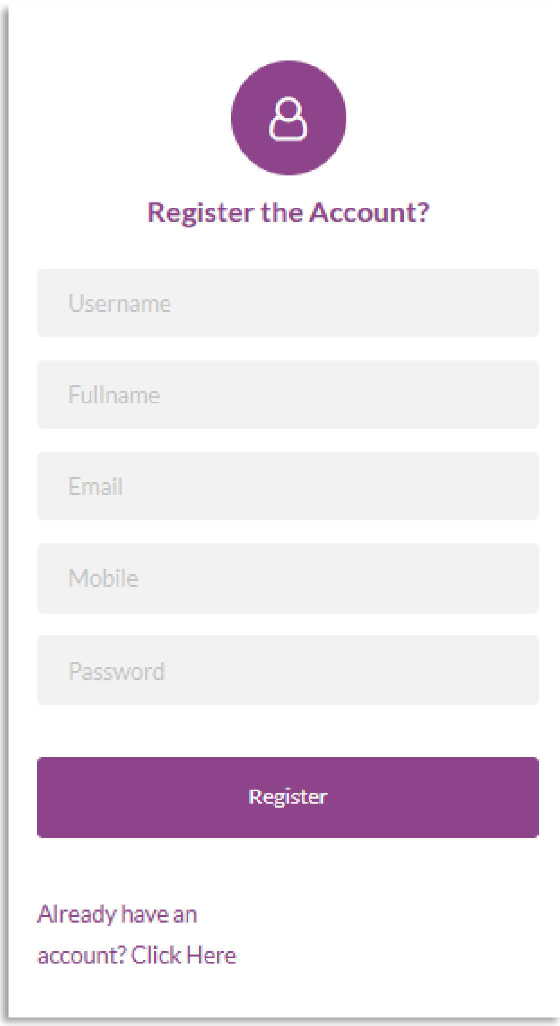


In Graph 1, accuracy is shown in light green, precision in blue, recall in light yellow, and the F1 score in green. The voting classifier has the best values for all metrics, making it better than the other algorithms. The graph above shows these details in a way that is easy to see.



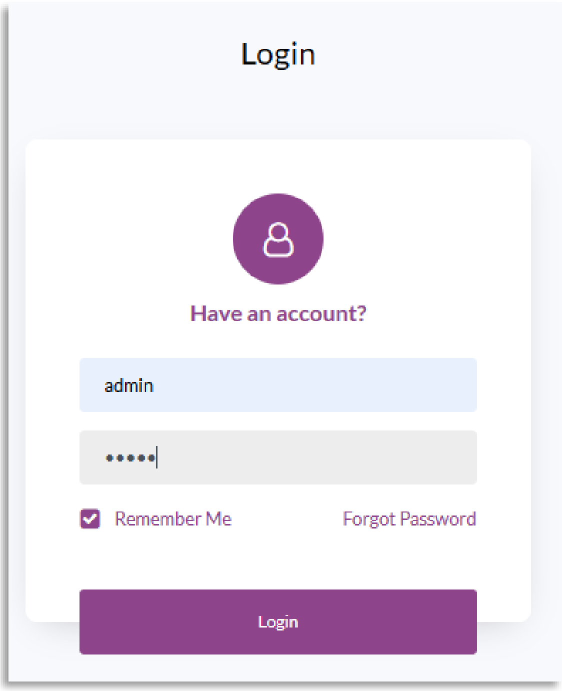
“Fig.3 Home Page”

in the picture above, you can see a user interface dashboard with navigation and a welcome message.



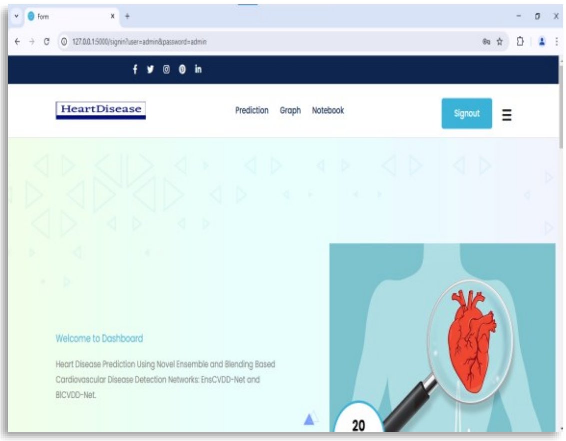
“Fig.4 Registration Page”

in the picture above, there is a sign-up form with sections for a username, name, email address, mobile number, and password buttons.



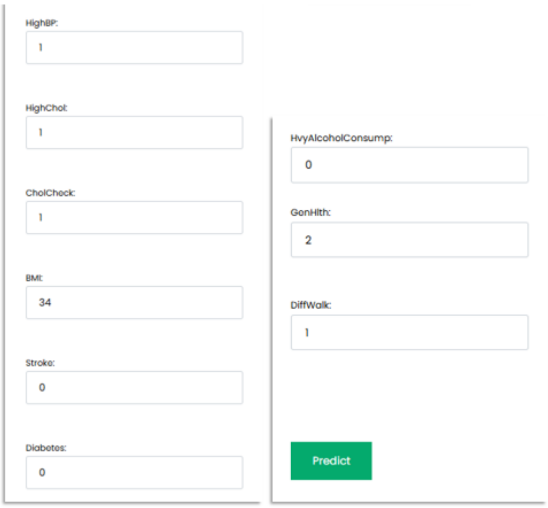
“Fig.5 Login Page”

In the picture above, there is a sign-in form with fields for a username and password, as well as "remember Me" and "Forgot Password."



“Fig.6 Main Page”

the main page dashboard in Fig. 6 above has navigation buttons for Prediction, Graph, notebook, and Signout.



"Fig.7 Upload Input Page"

in the above Fig. 7, there is a coordinate input field and an upload button.

"Fig.8 Predict Result for given input"

The above Fig. 8 shows the predicted result based on the test data.

5. CONCLUSION

In conclusion, the study shows that sophisticated ensemble methods can help make "cardiovascular disease (CVD) diagnosis more accurate. The proposed system uses the heart disease Dataset and Adaptive synthetic (Adasyn)" Oversampling to fix class imbalance. It combines data-driven methods to improve the accuracy of diagnoses. The voting Classifier is the best of "the models that were tested. It has an accuracy of 91.7%, a precision of 92.0%, a recall of 91.7%, and an F1-score of 91.8%". these results show that ensemble strategies can do better than individual models by combining their strengths and shortcomings in a smart way. The voting Classifier shows that it can handle complicated datasets and make good predictions, which makes it a promising method for finding CVD. This method can help doctors make faster and more accurate diagnoses, which will help lower the number of deaths caused by cardiovascular diseases. The effects show how important it is to use advanced computer tools in medical diagnostics.

The ***future scope*** is coming up with a superior version of the framework by mixing various other regions and employing more progressive techniques. prediction might also be enhanced with hybrid models that incorporate transfer learning and reinforcement learning. real-time data analytics and wearable health technology can also be followed in proactive monitoring and early intervention. incorporating new data sources of other regions into the technique will also make the framework more convenient and reliable.

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