Predicting The Occurrence Of Cardiovascular Disease Using The Novel Ensemble And Blend-Based Networks, EnsCVDD-Net and BlCVDD-Net

T. M. Kalathi [1], G. Viswanath [2], G. Swapna [3*] & T. Anil Kumar [4]

[1] P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,
ORCID-ID: 0009-0006-2158-1408; Email: tmkalathi2002@gmail.com

[2] Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,
ORCID-ID: 0009-0001-7822-4739; Email: viswag111@gmail.com

[*3] Assistant Professor, Apollo institute of Pharmaceutical Sciences, The Apollo University, Chittoor, India
ORCID-ID: 0000-0002-9340-4148; Email: swapnagv111@gmail.com

[4] Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,
ORCID-ID: 0009-0003-3312-3031; Email: anil.thumburu@gmail.com

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T. M. Kalathi [1], G. Viswanath [2], G. Swapna [3*] & T. Anil Kumar [4]

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ORCID-ID: 0009-0001-7822-4739; Email: viswag111@gmail.com

[*3] Assistant Professor, Apollo institute of Pharmaceutical Sciences, The Apollo University, Chittoor, India
ORCID-ID: 0000-0002-9340-4148; Email: swapnagv111@gmail.com

[4] Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,
ORCID-ID: 0009-0003-3312-3031; Email: anil.thumburu@gmail.com

ABSTRACT

Cardiovascular disease (CVD) is the most motive of demise globally, requiring well timed and unique analysis for effective medical intervention. this technique employs modern computational methodologies, using deep learning (DL) and machine learning (ML) strategies to enhance the accuracy and resilience of cardiovascular ailment (CVD) prediction systems. In contrast to standard machine learning strategies that rely notably on manual feature engineering, deep learning models possess the potential to independently extract complicated features from unprocessed records, rendering them noticeably appropriate for complex scientific datasets. The Adaptive synthetic Sampling (ADASYN) approach is applied to tackle troubles such as class imbalance, enhancing minority class representation and facilitating balanced learning. A dataset referring to heart disease is applied to educate and check the suggested class framework. Two novel ensemble-based architectures, namely EnsCVDD-Net and BlCVDD-Net, are introduced—one leveraging traditional ensemble strategies like bagging and boosting, and the other employing blend-based meta-learning techniques to combine multiple base classifiers effectively. The methodology incorporates major ML algorithms such as Random Forest (RF), XGBOOST, LightGBM, and Deep Learning models, including CNN and LSTM, to provide superior function representation. An efficient voting classifier for aggregate predictions from several models is also implemented, which improves decision-making accuracy. Metrics of evaluation, such as accuracy, download, and F1-score, demonstrate the advantages of file access over individual models. The system achieves 91.7% classification accuracy, 92.0% accuracy, 91.7% dismissal, and 91.8% F1 score, suggesting balanced performance across all rating metrics. The results highlight the adaptability and reliability of EnsCVDD-Net and BlCVDD-Net across varied clinical scenarios, reinforcing their potential in real-time medical diagnostic systems. This strategy underscores the promise of intelligent systems in delivering high-accuracy, automated predictions for early-stage cardiovascular disease detection.

Keywords: Cardiovascular disease detection, deep learning, heart disease, LeNet, gated recurrent unit, multilayer perceptron.

1. INTRODUCTION :

"Cardiovascular diseases (CVDs)" constitute a primary cause of mortality globally, posing a significant public health challenge. These disorders include many conditions that impact the heart and blood arteries, impairing the proper circulation of blood throughout the body. The heart, being one of the maximum vital organs, ought to work properly for survival; its failure or dysfunction due to illness can result in grave outcomes, including mortality or enduring impairments [2]. In latest decades, cardiovascular diseases have become increasingly frequent, affecting millions international. The "world health organization (WHO)" reports that heart disorders constitute 32% of all fatalities, with 85% of these resulting from heart attacks and strokes, emphasizing the urgent necessity for early intervention and diagnosis. The increasing prevalence of cardiovascular diseases is imposing great pressure on global healthcare systems, necessitating additional resources for diagnosis, treatment, and management.

Multiple risk factors facilitate the onset of "cardiovascular diseases (CVDs)", encompassing detrimental lifestyle choices such as suboptimal diets, inadequate physical exercise, obesity, tobacco use, and excessive alcohol intake [4]. These factors may result in illnesses such as hypertension, hypercholesterolemia, and insulin resistance, which considerably elevate the risk of heart disease. The delayed identification of cardiovascular diseases often requires intrusive interventions like angiography or bypass surgeries, which can induce patient suffering and elevate the financial strain on healthcare systems. Timely detection and diagnosis are essential to halt the advancement of these diseases, facilitating prompt therapies including pharmacotherapy, lifestyle modifications, and counseling. Nevertheless, precise prediction of heart disease is difficult due to the intricate interaction of factors such as hypertension, familial history, cholesterol levels, and diabetes, complicating early symptom detection for healthcare practitioners.

2. OBJECTIVES :

The primary objective is to build a reliable and accurate cardiovascular disease detection system by integrating advanced ensemble learning techniques, addressing class imbalance, and optimizing model performance across key evaluation metrics.

(1) To develop intelligent CVD detection models using ensemble-based learning techniques that integrate both deep learning and machine learning classifiers for robust performance across diverse clinical datasets.

(2) To address the issue of class imbalance using Adaptive Synthetic Sampling (ADASYN), thereby enhancing the learning capability of classifiers and improving overall diagnostic accuracy for minority CVD cases.

(3) To compare the performance of the proposed ENSCVDD-NET and BLCVDD-NET with typical individual classifiers utilizing additional metrics such as accuracy, memory, and F1-scone.

3. REVIEW OF LITERATURE/ RELATED WORKS :

Early identification of "cardiovascular disease (CVD)" has become a major priority due to the increasing occurrence of heart -related diseases and their significant effect on global mortality. Numerous studies focused on increasing the accuracy and efficacy of heart disease by using "machine learning fashion (ML)" and "deep learning (DL)", which have shown significant potential in analyzing large data sets and recognizing formulas that may escape conventional medical approaches. This research often integrates many methodologies, including the learning of the file, sequential selection of functions and hybrid models to improve the accuracy of prognosis.

Hymavathi et al. [11] presented a strategy for integrating a meta-function set that incorporates many machine learning models to improve the accuracy of heart disease predictions. By incorporating Meta functions, the model uses a variety of views of data, increasing durability and performance compared to conventional techniques. The authors illustrate the effectiveness of the method of learning the file, especially in connection with health care data, which often show noise and imbalance. The file method facilitates improving data variability control, leading to increased predictive accuracy to identify heart disease.

Jawalkar et al. [13] They examined the application of subordinate learning in conjunction with a stochastic gradient that increased to predict heart disease. This study emphasizes the ability of subordinate learning models to manage structured health data and use techniques such as an increase in gradient that excels in detecting complex formulas in large data sets. The use of this strategy to predict heart disease has brought remarkable results, which has shown the effectiveness of a stochastic gradient to minimize distortion and increase the performance of the model. The ability of the model to manage various health markers, including cholesterol, age and blood pressure, makes it a reliable method for early diagnosis of heart disease.

Chaurasia and Chaurasia [15] proposed an innovative set of elements based on the selection of elements to improve the accuracy of prediction in detection of heart disease. Their approach uses sequential selection of elements, a technique that reduces data dimensions while maintaining its significant attributes. This method prevents the model to be flooded with foreign data, which can lead to excessive and reduced accuracy. The authors integrated sequential selection of elements with a file method for the development of a resistant predictive model, emphasizing the importance of functional engineering in healthcare data sets, where excessive dimensional data often represent an obstacle to effective analysis.

Dileep et al. [17] introduced an automated model for predicting heart illness that employs a "cluster-based bi-directional long brief-term memory (C-BiLSTM) algorithm". LSTM networks are extensively utilized in time-series data, where temporal connections among data points are crucial. The scientists enhanced the model's accuracy in heart disease prediction by incorporating clustering into the LSTM architecture. The C-BiLSTM algorithm effectively captured both short-term and long-term dependencies in health data, resulting in enhanced prediction accuracy. This method illustrated the efficacy of deep learning approaches, especially LSTM networks, in managing intricate datasets containing sequential and temporal data.

Sudha and Kumar [19] used hybrid architecture of CNN and LSTM to predict heart disease. Convolutionary neural networks (CNN) are generally used for image processing; however, the authors modified them for application in medical data sets. They integrated CNN with LSTM networks to earn the benefits of both models: CNN to extraction of elements and LSTM for sequential data analysis. The CNN-LSTM hybrid model showed increased performance compared to conventional machine learning models, and effectively captured both local styles in data (via CNN) and long-term dependence (via LSTM). This hybrid method has shown significant efficiency in predicting heart disease assimilations of both increased characteristics and time correlations within health data.

Sharma et al. [21] introduced a hybrid deep neural network model optimized through randomized search go-validation for the prediction of coronary heart disease. The model incorporated various layers of neural networks and employed go-validation methods to refine hyperparameters, enhancing the model for superior prediction accuracy. Through the implementation of cross-validation, the authors ensured that the model exhibited robust generalization to novel data, an essential consideration in practical applications. This hybrid model underscores the capabilities of neural networks, particularly deep neural networks, in forecasting complex health situations characterized by nonlinear and intricate variable connections.

Ogundepo and Yahya [23] performed an extensive performance evaluation of various supervised classification models for predicting heart disease. Research has evaluated several models, including "decision -making trees, random forests, support of vector machines and logistics regression", their efficiency in proper "prediction of heart disease" based on various health indices. Their finding has indicated that such random forests, such random forests, regularly exceed models with one classifier, emphasizing the efficiency of integrating multiple models for increased predictive performance. This study stresses the need of selecting the optimal machine learning algorithms to predict cardiac disease, as the complexity of the data necessitates a comprehensive assessment of the benefits and drawbacks of various methods.

These findings indicate that "machine learning and deep learning" are gaining prominence in healthcare, particularly in the diagnosis of cardiac disease. The integration of LSTM networks, hybrid models, and ensemble methods improved forecasting accuracy. These algorithms identify subtle patterns in complex, high-dimensional data for precise diagnosis and rapid response. Advanced algorithms, databases, and real-time analytics will enhance the prognosis of heart diseases for dependable healthcare.

Table 1: Literature Survey Comparison Table

Sl. No	Area & Focus of the Research	The result of the Research	Reference
1	Meta-function ensemble for robust heart disease prediction accuracy improvement.	Enhanced performance using multiple ML models and data perspectives.	K. Hymavathi, S. H. Mehanoor, G. SrinivasEt.al., (2024). [11]
2	Subordinate learning with stochastic gradient boosting for heart disease.	Accurately detects complex patterns in structured health datasets.	A. P. Jawalkar, P. Swetcha, N.

			Manasvi., et.al., (2023) [13]
3	Sequential feature selection and ensemble fusion for prediction accuracy.	Reduced dimensionality while maintaining important predictive attributes.	V. Chaurasia and A. Chaurasia et. Al., (2023) [15]
4	Cluster-based BiLSTM model for sequential health data prediction.	Improved short and long-term pattern recognition in diagnosis.	P. Dileep, K. N. Rao, P. Bodapati, et.al., (2023) [17]
5	CNN-LSTM hybrid architecture for capturing spatial-temporal medical features.	Achieved higher accuracy than traditional ML techniques.	V. K. Sudha and D. Kumar et. al., (2023) [19]

4. MATERIALS AND METHODS :

The aim of the proposed approach is to create a comprehensive framework for accurately identifying “cardiovascular disease (CVD)” using advanced “machine learning (ML)” and “deep learning (DL)”. This system merges a diverse field of algorithms, including LENET, GRU, Enscvdnet, BicVDD-Net, Lstm, Bilstm, CNN+Lstm, Adaboost, Knn, Knn, SVM, XGBOOST, Naive Bayes, Logistic Regression and Volus Analysis Classing. A heart disease data set is used and adaptive synthetic (Adanyn) is implemented to correct the class imbalance and improve the model training. This approach uses DL for automatic element extraction and integrates it with the predictive power of ML models to effectively manage huge and complex data sets with increased accuracy. File models, namely ENCVDDNET and BICVDD-NET, are designed to take advantage of free advantages of separate algorithms that offer a thorough and efficient approach to detecting and diagnosing heart diseases.

Fig 1: Proposed Architecture

Illustration (Fig. 1) represents a standard machine learning process. The procedure begins with a data file, which undergoes basic processing to clean and prepare it for analysis. This pre-processing phase could include data processing, visualization, and sampling. The data file is then separated into two subsets: training and testing. Machine learning models are designed and trained using the training dataset. Once the training is complete, the models are tested to determine their performance using measures such as accuracy, download, and F1-jump. These evaluation indicators provide insight into the model's ability to forecast accurately and classify data correctly.

4.1 Dataset Collection:

This study uses the data set of data on "heart disease diseases" from the 2015 risk (BRFS) system, which provided the Centers for Control and Prevention of Diseases (CDC) [13]. This comprehensive data file includes fitness records of more than 253,680 individuals and includes 22 attributes, including ("HeartDisisaotattack", "HighBP", "Highchol", "Cholcheck", "BMI", "Smokeer" "Menthlth", "Physhlth", "Diffwalk", "Sex", "Age", "Education" and "Income"). It offers significant knowledge about the classification of binary heart diseases, acting as a basic source for health -related research.

Table 2: Dataset Collection Table – Heart Disease Data

	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

4.2. Pre-Processing:

Preliminary data processing is a necessary phase of data file preparation for analysis. This process involves cleaning data by managing missing values, removing duplicates and removing foreign elements, so preparing a data file for model training and ensuring accurate and reliable results.

4.2.1 Data Processing

The data processing phase commences with the identification of null values, which are then eliminated to maintain the dataset's integrity. Subsequently, duplicates are recognized and addressed, hence minimizing repetition in the facts. Upon eliminating duplicates, the dataset indices are recalibrated to ensure consistency. Ultimately, categorical columns are examined to determine whether features require encoding or transformation for conformity with the model.

4.2.2 Data Visualization

data visualization entails the construction of graphical representations of datasets to reveal patterns, trends, and relationships. methods including histograms, bar charts, and scatter plots are utilized to examine the distribution of attributes such as 'Age', 'BMI', and 'HeartDiseaseorAttack'. This aids in comprehending the dataset's architecture and pinpointing critical determinants of heart disease.

4.2.3 Data Sampling

To rectify class imbalance in the dataset, Adasyn oversampling is employed, producing synthetic data points for the minority class. This method guarantees equitable representation of both classes, hence augmenting model efficacy by mitigating overfitting and promoting generalization. it is especially beneficial in datasets characterized by skewed distributions, such as those used for heart disease categorization.

4.3. Training & Testing

The data file is divided into training and test sets in a ratio of 80:20. As a result, 80% of the data is assigned to the model training to recognize the formulas and generate predictions, and the remaining 20% is specifically for testing and evaluate the efficiency of the model on new data. This department ensures that the model is trained on a substantial data segment and at the same time maintains an impartial evaluation with a different test kit and therefore increases the generalization and resistance of the trained model.

4.4. Algorithms:

[19] LENET is a “convolutional neural network (CNN)” developed for applications of element extraction and image processing. It is used to investigate structured formulas in data, which is effective for identifying complex aspects in medical display or tabular data format for diagnosis of cardiovascular diseases.

GRU“GatedRecirrent Unit (GRU)” is a type of “recurring neural networks (RNN)” designed to capture sequence dependencies in time series data. It is used to explore the history of patients or temporary trends in health data and provides effective learning with less computing complexity compared to conventional RNN.

EnsCVDDNetintegratesvariousDL networks into an ensemble to improve predictive accuracy. It consolidates the advantages of separate models, emphasizing the extraction of complex patterns from high-dimensional cardiovascular information for enhanced disease diagnosis accuracy.

BICVDD-Netincorporates a combination of classifiers and DL frameworks, highlighting context-sensitive predictions. It is designed for the extraction and analysis of intricate correlations in cardiovascular data, guaranteeing accurate categorization and strong decision-making.

LSTM"long short-term memory" networks manage sequential data characterized by long-term dependence. [18] they are utilized to identify intricate temporal patterns in patient health information, facilitating accurate prediction of cardiovascular risks.
BiLSTMBidirectional LSTM handles sequential data in both forward and backward directions, hence augmenting contextual comprehension. It is utilized to examine dynamic and contextual patterns in patient data, enhancing the identification of cardiovascular disease indicators.
CNN+LSTM The architecture integrates convolutional layers for spatial feature extraction with LSTM layers for sequential analysis [15]. This hybrid methodology is applied for datasets exhibiting both spatial and temporal attributes, such as sensor measurements or multi-modal health information.
AdaBoostAdaptive Boosting enhances classification by iteratively amalgamating weak learners. It is utilized to enhance forecasts and augment overall model efficacy, ensuring a balanced methodology for managing varied cardiovascular data characteristics.
KNNThe k-Nearest neighbor's algorithm classifies data points according to their closeness to tagged instances. [16] It is utilized for clear and interpretable forecasts in datasets with distinct clusters, providing insights into cardiovascular health trends.
SVMsupport Vector machine generates hyperplanes to delineate data into distinct classes. It is beneficial for binary and multi-class classification, examining cardiovascular data to distinguish between healthy and at-risk patients [17].
XGBoostThe extreme increase in the gradient (XGBOOST) is a sophisticated technique of ensemble learning that constructs decision -making trees in an iterative way. It is used for its speed and accuracy in the management of structured health data and determines basic factors affecting cardiovascular disease.
Naive Bayesemploys probability-based categorization to examine correlations among features. It is utilized for rapid and efficient predictions in cardiovascular datasets, particularly in cases along with categorical or independent characteristics.
Logistic Regressioncalculates the likelihood of categorical results based on input variables. It is utilized to forecast binary outcomes, such as the existence or nonexistence of cardiovascular ailments, predicated on essential risk elements.
Decision Tree[8] establishes a hierarchical framework to generate predictions based on feature divisions. It is utilized for intuitive and interpretable classification of cardiovascular data, finding key contributing components.
Voting Classifierconsolidates forecasts from various models to enhance precision and resilience. It is employed to harness the advantages of distinct algorithms, resulting in enhanced efficacy in cardiovascular disease detection.

5. RESULTS AND DISCUSSION :

Accuracy: The test's accuracy refers to its capacity to correctly distinguish between patients and healthy cases. To measure the test's accuracy, determine the ratio of true positives to real negatives in all analyzed cases. This can be mathematically stated as follows:

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

Precision: The accuracy evaluates the share of precisely classified cases among cases identified as positive. As a result, the formula for calculating accuracy is expressed:

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

Recall: Recall is a machine learning metric that measures the model's ability to recognize all relevant examples from a given class. It is the proportion of exactly predicted positive observations to total genuine positives and provides insight into the model's performance in detecting the presence of a specific class.

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

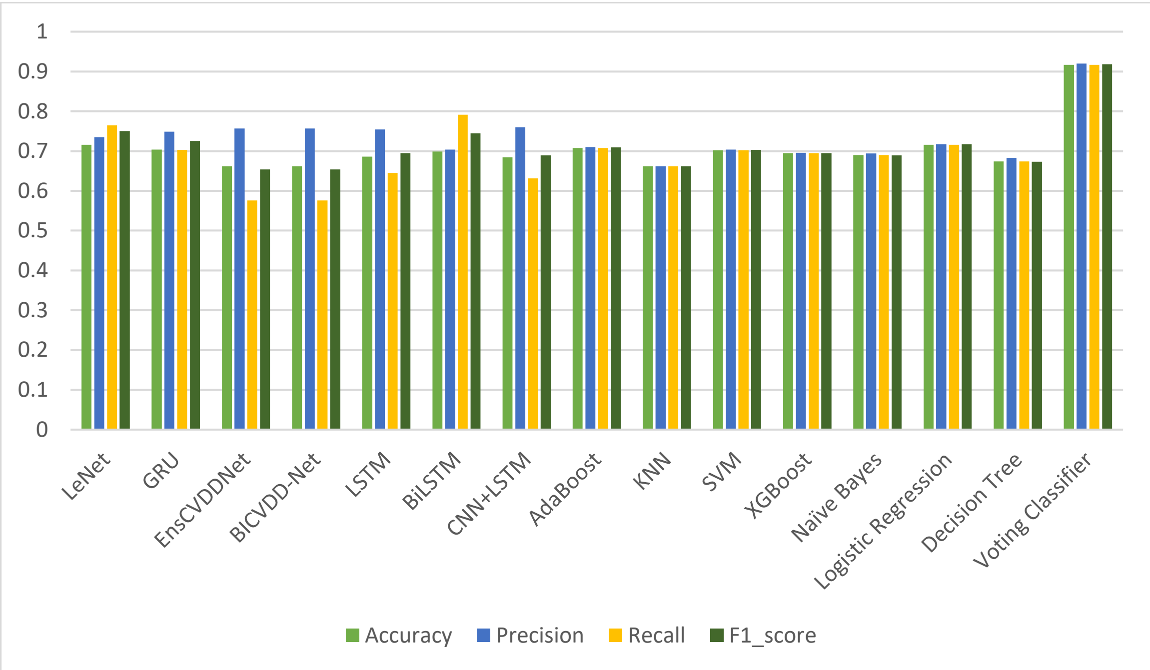
F1-Score: The score F1 is a metric for evaluating the accuracy of the machine learning model. It integrates the metrics of accuracy and model. The metric of accuracy quantifies the frequency of real predictions generated by the model throughout the data file.

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

We assess the accuracy of power measurements, downloads, and F1-scores for each algorithm mentioned in Table 1. The voting classifier achieves the highest score. In addition, the table below offers many methodologies for comparison analysis.

Table 3: 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
NaïveBayes	0.690	0.694	0.690	0.689
LogisticRegression	0.716	0.717	0.716	0.717
DecisionTree	0.674	0.683	0.674	0.673
Voting Classifier	**0.917**	**0.920**	**0.917**	**0.918**



Graph 1: Comparison Graphs

Graph 1 illustrates accuracy in light green, precision in blue, recall in light yellow, and the F1 score in green. The voting classifier surpasses the other algorithms across all metrics, exhibiting the greatest values relative to the other models. The graph above vividly illustrates these details.

6. CONCLUSION :

The study conclusively illustrates the efficacy of modern ensemble approaches in enhancing the precision of "cardiovascular disease (CVD)" diagnosis. The proposed methodology utilizes the heart disease Dataset and mitigates class imbalance via Adaptive synthetic (Adasyn) Oversampling to improve diagnostic accuracy through data-driven methodologies. The voting Classifier exhibits the superior performance among the assessed models, with an "accuracy of 91.7%, precision of 92.zero%, recall of 91.7%, and an F1-score of 91.8%". These results underscore the power of ensemble approaches to surpass individual models by adeptly amalgamating their strengths and mitigating flaws. The voting Classifier demonstrates its efficacy in managing intricate datasets and providing dependable predictions, establishing it as a valuable instrument for precise CVD identification. This method can greatly enhance prompt and accurate diagnosis, hence helping to decrease mortality rates linked to cardiovascular diseases. The results underscore the need of utilizing sophisticated computational techniques in medical diagnostics.

The future scope involves augmenting the framework by incorporating various areas and sophisticated strategies. Investigating hybrid models that integrate transfer learning and reinforcement learning may enhance predicted accuracy. Furthermore, utilizing real-time data analytics and wearable health technology facilitates proactive monitoring and early intervention. Incorporating heterogeneous information from multiple geographical regions would improve applicability and robustness, hence facilitating more tailored and effective cardiovascular disease management techniques.

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