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AI CARDIONET- A LIGHTWEIGHT STACKING ENSEMBLE FRAMEWORK FOR EARLY DETECTION OF CARDIOVASCULAR DISEASE

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ABSTRACT
Heart disease persists as a primary contributor to mortality worldwide, highlighting the urgent need for faster and more accurate predictive tools in clinical practice. Improvements in diagnostic accuracy could be possible with the help of new AI technologies and supporting cardiology decision-making. This study introduces AI-Cardiologist, a supervised learning framework designed to improve early detection of cardiovascular disease using structured medical records. Because of the problems with using outdated models in terms of scalability and interpretability, a novel lightweight stacking ensemble algorithm, CardioStackNet. The method integrates logistic regression, decision trees, and use of logistic regression as the meta-learner and Gaussian Naïve Bayes as the base-learning algorithm for final predictions. A dataset comprising over 70,000 patient records with features such as cholesterol levels, age, blood pressure, body mass index (BMI), and lifestyle indicators was utilized. Following comprehensive preprocessing and feature engineering, the models underwent training and assessment using stratified train-test splits to ensure balanced performance across classes. Experimental results demonstrated that CardioStackNet achieved a predictive accuracy exceeding 95%, significantly outperforming standalone classifiers about recall and F1-score, while maintaining computational efficiency. The findings underscore the effectiveness of lightweight stacking ensembles in practical diagnostic settings, especially those with limited resources clinical environments. Importantly, the proposed system guarantees not only elevated precision but also interpretability and ease of deployment, rendering it a promising candidate for next-generation AI-powered cardiovascular diagnostics.
Keywords- cardiovascular disease; Artificial Intelligence; Machine Learning; Stacking Ensemble; Logistic Regression; Decision Trees; Gaussian Naïve Bayes; Predictive Diagnostics; Medical Data Mining; Clinical Decision Support

INTRODUCTION

A primary cause of mortality on a global scale, cardiovascular disease (CVD) is infamously dangerous. Particularly, coronary artery infections—a leading cause of death—are a consequence of impaired blood vessel function brought on by heart illness [1]. More people around the world are now at risk for developing heart failure, a complex clinical illness. Electrocardiograms (ECGs) rely significantly on the early phases of heart failure evaluation and diagnosis in hospitals and cardiac centers. Imagine the ECG as a standard instrument. Healthcare systems prioritize early identification of heart disease [2]. The early identification of CVD signs poses a significant problem for clinicians. CVD is a main cause of mortality for numerous individuals globally. Timely attention is required since heart disease is a serious problem. It is difficult to diagnose cardiac disease due to the various factors influencing health, include hypercholesterolemia, arrhythmia, and hypertension, and many more [3]. Cardiovascular disorders are frequently traded for heart diseases. Heart disease, stroke, and angina are symptoms of vascular disease, which is characterized by constricted or blocked blood vessels. There are various forms of cardiac disease, including those that impact the heart's rhythm, valves, or muscles [4]. Heart disease is among the top killers in the world. Countless lives are lost each year due to this illness. The World Health Organization reports that 17.9 million people die each year from heart disease. Using image classification in conjunction with the many existing technologies and methods for heart disease screening can yield even better outcomes. In the present day, picture categorization has become an important issue. Adding a label or labels to a picture is a fundamental task in pattern recognition and computer vision [5].
In order to reduce death rates, a Machine Learning (ML) system can use clinical data to make early predictions for CVD. A number of recent research have employed different machine learning algorithms to diagnose CVD or to assess the severity of the condition in patients. Despite these studies' encouraging findings, not a single one of them addressed the need to optimize ML models for CVD diagnosis and severity level categorization [6]. Globally, heart disease claims a disproportionately high number of lives due to its lethal character. A reliable and early technique of identification is crucial in the fight against heart disease. Signals from impedance cardiography (ICG), cardiac

sonography (CS), computed tomography (CT), magnetic resonance imaging (MRI), and electrocardiograms can all help doctors identify hypertension heart disease in a patient [7]. Globally, the great majority of deaths are caused by CVD and disorders. It is possible to save more lives if they can be predicted and identified earlier. The ECG is a popular, inexpensive and less intrusive technique for detecting cardiac problems by monitoring the heart's electrical activity [8]. According to publicly available statistics, CVD is the top killer on a global scale. Coronary arrhythmia is one of the leading causes of heart issues, which is characterized by irregular heartbeats [9]. An important problem in the modern world and a major killer all around the globe is heart disease. It is now possible to diagnose early stages of cardiac illness using the developments in ML applications have made it possible to analyze electrocardiograms (ECGs) and patient data. It becomes difficult for classical ML to function impartially when dealing with ECG and patient data that is frequently unbalanced [10].
As part of managing disease, it is crucial to identify and predict whether healthy persons could potentially develop CVD. It is very possible to improve disease outcomes by early identification and diagnosis of CVD by accessing the extensive health data on CVD that is now available in hospital databases [11]. All living things face various dangers as they experience life. One of the most significant dangers is heart disease to human and animal life because of its high death rate. Among the most serious diseases in the world, it requires a thorough diagnosis and extensive treatment. As a whole, it has affected healthcare systems globally in a substantial way, wealthy and poor alike [12]. Rapid and preventative medical treatment is provided to at-risk patients through remote healthcare applications built on the Internet of Things (IoT). Predicting cardiac disease, however, is no easy feat, and correct diagnoses are rare [13]. ML model for the identification of cardiovascular disease in persons with medium to high risk, utilizing information from a Greek cohort of 542 patients afflicted with rheumatoid arthritis, diabetes, arterial hypertension, and other ailments. The ML model incorporates phenotypes obtained from carotid and femoral ultrasound pictures with traditional or laboratory-based blood indicators [14]. One out of every four deaths on earth are caused by CVD. Automated ML-Based Early Diagnosis of Heart Disease system can reduce mortality rates by analyzing clinical data. The inability to accurately analyze application of predictive data in various real-world contexts, such as the detection of cardiovascular illness is due, in large part, to the class imbalance and high dimensionality problems that have long plagued ML [15]. Clinical settings face the challenge of detecting heart disease, which unfortunately leads to higher mortality rates. Analyzing ECG signals is a common part of current detection methods, but it is important to process the data accurately and extract features from it. Processing time and accuracy are two areas where traditional technologies fall short [16]. Prevalence of cardiovascular disease has been increasing for some time, and experts predict it will keep doing so. Heart disease is quickly rising to the level of a major public health concern. An important problem for the health of people in countries with poor or medium incomes, CVD causes an annual uptick in hospital admissions [17]. A variety of aberrant cardiac problems, together known as heart illnesses, are responsible for approximately one out of every four fatalities. Nevertheless, the manual analysis of data gathered from several clinical procedures makes the diagnosis of CVDs a laborious process. In an effort to shorten the diagnostic process while also enhancing the accuracy of those findings, medical professionals need innovative methods for using automated systems to identify these anomalies in heart conditions affecting humans [18]. Predicting cardiac problems is one of the most challenging medical tasks. Discovering the root cause requires significant investment of time and energy, particularly from medical professionals [19]. The global burden of disease and death is disproportionately borne by CVDs. If important biomarkers and function parameters are identified quickly and accurately, they can provide light on the physiological or pathological processes of CVDs [20].

LITERATURE SURVEY

Heart disease is a major killer all around the world, often known as heart disease. It is common practice to mine EHRs for insights that can improve machine learning algorithms' predictive abilities. on particular, Machine Learning makes a substantial impact on addressing prediction-related problems across several industries, including healthcare. There is a pressing need to put the vast amounts of publicly available clinical data to use for the benefit of all people [18]. For validation, it uses a 5-fold cross-validation approach. There is a comparison of the four methods. Utilizing the Long Beach V and UCI Kaggle, assess the models' effectiveness in addition to the datasets for Cleveland, Hungary, and Switzerland [19]. Potential for early prediction and rapid diagnosis of CVDs has been demonstrated by nano sensors that combine the benefits of nanomaterials with sensing platforms. In [20], compiles the most up-to-date information on electrochemical, optical, pressure, and paper-based nano sensors that have been developed for the detection of CVDs. Patients with cardiovascular problems are best treated when complications are identified early. Early detection of heart problems has previously made use of several machine learning technologies. Unfortunately, there is a lack of effective and efficient heart disease detection using current data-driven ML methods. The detection performance is maximized by developing a strong by utilizing ensemble learning, Stacking Ensemble Learner (SEL). Following a preliminary admission, the SEL technique can determine if a patient requiring emergency hospitalization due to cardiac issues is necessary. The SEL model makes use of the XGBoost as a meta-learner to guarantee that the prediction outcomes are robust and highly accurate over various runs [21]. Cardiovascular disorders, ischaemia, anomalies of the heart's chambers, abnormal heart rate measurement, biometric identification, and many more conditions can be diagnosed and detected by analyzing ECG data. There are a lot of potential sources of noise that can weaken ECG signals, which can alter the morphological characteristics of the signal and cause incorrect diagnosis and therapy. As part of processing ECG signals, noise removal is required. Accurate information regarding the human heart's cardiac health can be derived from denoising the ECG signal enables accurate morphological feature detection [22]. To assess and forecast the likelihood of heart illness, a model called QPSO-SVM was suggested, which combines integration of the SVM classification model with the quantum-behaved particle swarm optimization (QPSO) technique. The initial step in data preparation was to apply effective scaling algorithms and convert nominal data to numerical data. After that, finding the optimal features for the SVM fitness equation requires transforming it into an optimization problem and then applying the QPSO algorithm [23]. An integrated system for the identification of cardiac disorders by use of audio recordings from healthcare providers is proposed. The four-layer proposed framework includes multiple layers, including one for segmentation, one for features extraction, one for learning and optimization, and finally, one for export and statistics. Different lengths of time and directions (forward and backward) of segmentation as a unique segmentation technique in the first layer. A total of eleven datasets containing fourteen thousand sixteen numerical features were produced by means of the suggested method. Features are extracted by the second layer. Both numerical and graphical properties are examined in the final datasets [24]. CAD is a global epidemic, disproportionately impacting countries with poor or medium incomes. In order to get around the following restriction, a low-cost app for diagnosing heart problems is required. For the benefit of generations to come, a model based on RCNN has been developed. Important data for the prediction of heart disease is extracted using various forms of cognitive technologies and deep learning [25].

Effective treatment and prevention of cardiac problems require early detection and correct diagnosis. The capacity of artificial neural networks (ANNs) to learn intricate patterns from data has made them a potent tool for the identification of cardiac illness. The area, seeing federated learning as a tool for collaborative model building, incorporating integrating AI-powered decision-support systems into standard healthcare operations, and improving the interpretability of models via explainable AI methods [26]. A model that determines the likelihood of CVD and helps raise awareness or diagnose the condition. Elman, feedforward, cascade forward, long- and short-time memory, and neural networks are used to compare the algorithms' performance [27]. A compact CRNN architecture that can automatically identify five types of aortic stenosis, mitral stenosis, mitral regurgitation, and mitral valve prolapse can be detected with cardiac auscultation using a raw PCG signal. This is all possible because of the two stages of learning: representational learning and sequence residual learning the process is now fully automated. The representation learning phase makes use of three concurrent CNN pathways to study the salient features from varying the receptive fields by means of 2D-CNN based squeeze-expansion, and to acquire the PCG's coarse and fine-grained characteristics [28]. After going through the inclusion and exclusion criteria, 58 of the 4,372 papers that came up in the first search were chosen to be read in full in order to address the research topics. The primary outcomes are: Out of the 58 papers that were chosen, 34 (58.62%) discuss the use of ML algorithms in healthcare, while 46 (79.31%) discuss techniques of monitoring heart rate using wearable sensors and digital stethoscopes [29]. The model for predicting cardiac problems using machine learning that can concurrently handle binary and many classifications. Initially, develop a gradient boosting decision tree (GBDT) approach that contains fuzzy logic as well as GBDT in order to simplify data and enhance the predictability of binary classifications with more generalizability. To prevent overfitting, we next combine Fuzzy-GBDT with bagging. Heart disease severity is further classified using an approach to multiclassification prediction using Bagging-Fuzzy-GBDT [30].

An efficient and highly accurate paradigm for the prediction of cardiovascular disorders is proposed, MaLCaDD, which stands for CVD Diagnosis using ML. For example, from the outset, the system handles data imbalance (via the Synthetic Minority Over-sampling Technique - SMOTE) and missing values (by the mean replacement technique). Afterwards, the Feature Importance approach is employed to pick features. Lastly, a K-Nearest Neighbour (KNN) and Logistic Regression (LR) classifier ensemble [31]. Acute CVD, particularly one of the leading causes of mortality on a global scale is ST segment elevation myocardial infarction (STEMI). It is critical to diagnose and treat these cases promptly in order to prevent mortality and morbidity because these conditions are quick and deadly. It is of the utmost importance to distinguish between infectious risk and cardiovascular problems during the 2019 coronavirus pandemic (COVID-19). This can be achieved and remote monitoring made possible through the use of wearable devices-based mobile health (mHealth) for early screening and real-time monitoring to handle this incredible problem [32]. Disease prediction in fog computing using blockchain technology for safe healthcare services. Prediction takes diabetes and cardiovascular illnesses into account. At first, a Blockchain is used to store the health records of patients that have been retrieved from Fog Nodes. At first, the patient health records are clustered using the innovative rule-based clustering algorithm. Finally, FS-ANFIS is employed to predict diabetes and cardiovascular diseases; it is an adaptive neuro-fuzzy inference system that relies on feature selection [33]. The advent of computerized ECGs in the last several decades has led to mounting evidence that these abnormalities can be detected using ML. By mining a database of about forty thousand electrocardiograms (ECGs) annotated by world-renowned cardiologists, our algorithms are able to differentiate between seven different signal types: normal, atrial fibrillation, tachycardia, bradycardia, arrhythmia, other, and noisy [34]. A deep learning model built using Keras that can calculate densities with dense neural network topologies ranging from three to nine layers. Every hidden layer makes use of 100 neurones and the Relu activation function. The analysis is conducted employing a variety of heart disease datasets as benchmarks. The assessment is carried out on all datasets pertaining to cardiovascular disease, which includes both individual and ensemble models. Also, the dense neural network is tested on all datasets using important parameters including f-measure, specificity, accuracy, and sensitivity. Different attribute categories cause different layer combinations to perform differently across datasets [35].

Ref	Algorithm	Dataset	Accuracy
[2]	XGBoost algorithm	Hospital Database	-
[3]	XGBoost Algorithm	70000 patient's dataset	88.70%
[4]	Random forest classifier algorithm		83%
[5]	**Deep Convolutional Neural Network**	public UCI heart-disease dataset	91.7%
[7]	Deep learning-based ensemble model	PTB-ECG and MIT-BIH	97.4%
[8]	convolutional neural network	public ECG images dataset	98.23%
[11]	Catboost model	cutting-edge CVD Diseases dataset	90.94%
[13]	bidirectional-gated recurrent unit (BiGRU) attention model	Framingham's and Statlog heart disease dataset	99.90%
[16]	Gradient Squirrel Search Algorithm-Deep Maxout Network (GSSA-DMN)	ReliefF on the pre-processed dataset	93.2%
[19]	XGBoost Classifier without GridSearchCV	Hungary, Switzerland &; Long Beach V and UCI Kaggle	98.05%
[21]	robust Stacking Ensemble Learner (SEL) using ensemble learning	Multiple Dataset	88%
[23]	quantum-behaved particle swarm optimization (QPSO) algorithm	Cleveland heart disease dataset	96.13%
[24]	Grid Search and Aquila Optimizer (AO) - CNN	11 datasets with 14,416 numerical features	99.17%
[28]	2D-CNN based squeeze-expansion	PhysioNet/CinC 2016 challenge dataset	86.57%
[33]	adaptive neuro-fuzzy inference system (FS-ANFIS)	dimensionality of the dataset	81%

METHODOLOGY

The proposed approach used to create the forthcoming system for predicting cardiac problems is designed to ensure scientific rigor, reproducibility, and applicability in real-world clinical contexts. The first step was to obtain a validated dataset on heart disease. This dataset would contain clinical, physiological, and demographic variables like age, sex, cholesterol, and blood pressure, chest pain type, and other cardiovascular indicators. The dataset served as the primary foundation for model development, with its selection guided by relevance to cardiovascular health and availability of established ground truth labels for disease presence.

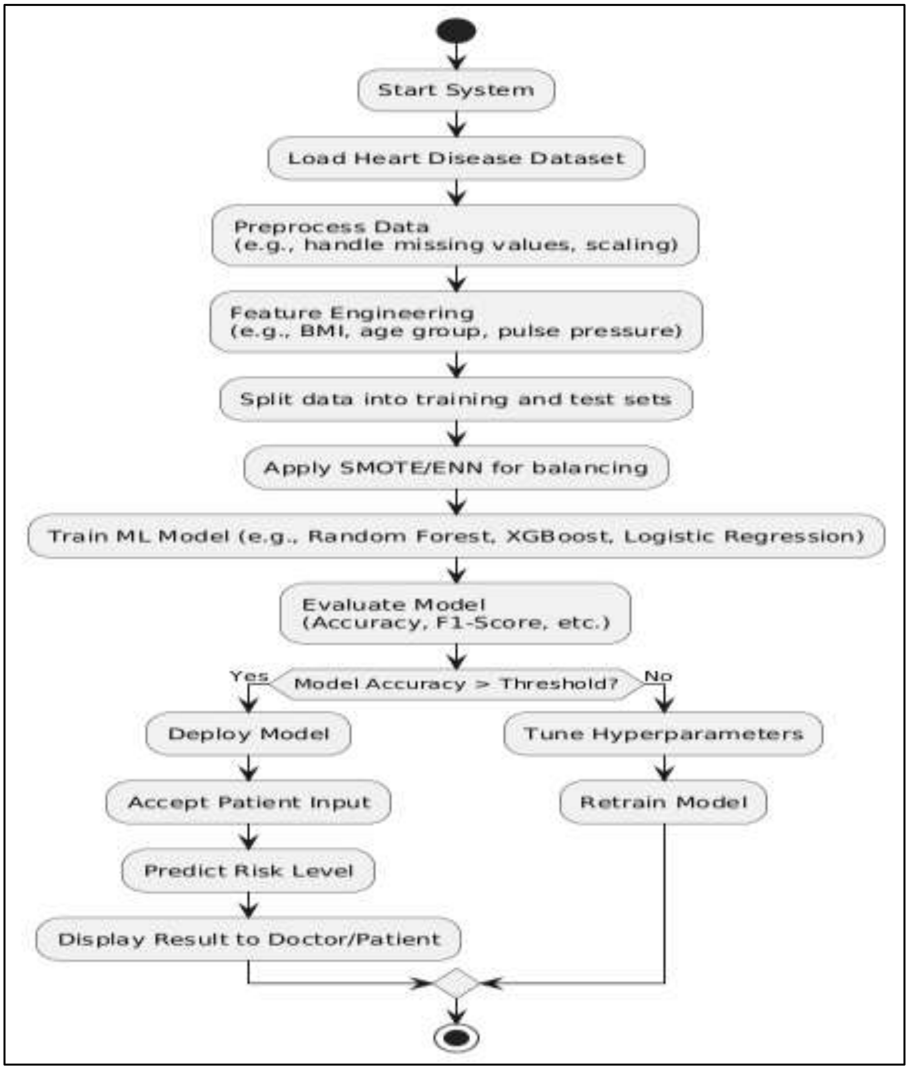

Figure 1. Heart Disease Prediction System Workflow

Figure 1 illustrates the flowchart delineates the sequential procedure of a ML-based cardiac disease prediction system. The procedure commences with dataset loading, preprocessing, and feature engineering, then followed by training with methods such as Random Forest or XGBoost. Upon assessing model accuracy, it either advances to deployment or undergoes retraining through hyperparameter optimization. The completed system receives patient input, assesses the risk level, and presents the outcome to healthcare practitioners for decision-making.

In the initial phase, data preprocessing was undertaken to address the challenges of incompleteness, heterogeneity, and noise inherent in medical data. Missing values were treated using imputation methods such as mean or median replacement, while normalization techniques were applied to continuous features to standardize measurement scales. Outlier detection strategies were employed to minimize distortions that could arise from extreme values. Categorical attributes, including chest pain type and thalassemia, were encoded numerically through one-hot encoding or label encoding in order to facilitate compatibility with machine learning algorithms. This stage ensured that the dataset was clean, consistent, and adequately structured for subsequent analysis.

Following preprocessing, feature engineering was conducted to enhance the predictive capacity of the dataset. Derived variables such as body mass index (BMI), age group categorizations, and pulse pressure were introduced to capture clinically significant relationships. In addition, interaction features were generated to model non-linear dependencies, such as the combined effect of cholesterol and age on cardiovascular risk. This process was guided by domain knowledge, ensuring that the engineered features reflected meaningful clinical constructs and thereby improved the generalizability of the model to new data sets.

In order to maintain the same ratio of positive to negative cases in both the training and testing subsets, the improved dataset was then divided into them using stratified sampling techniques. A typical division followed an 80:20 or 70:30 ratio, enabling enough information to train the model and guarantee reliable results when tested on new cases. Considering the prevalent problem of class imbalance in healthcare datasets, where the quantity of unfavorable situations typically outweighs the positive cases, oversampling and under sampling strategies were adopted.

Specifically, Edited Nearest Neighbor (ENN) approach integration with the Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic minority class samples while removing noisy or borderline examples from the majority class. This approach ensured a balanced dataset that reduced bias and enhanced sensitivity to positive predictions, which is critical in medical diagnosis. The next stage involved the training of machine learning models. A number of algorithms were utilized, such as Logistic Regression, XGBoost, and Random Forest, selected for their proven effectiveness in classification tasks of medical significance. Each model was trained on the preprocessed and balanced training set, learning to identify complex patterns indicative of heart disease risk. The training process was carefully controlled to prevent overfitting, with techniques such as cross-validation employed to assess generalization during development.

Model evaluation was conducted using a comprehensive suite of performance metrics. Accuracy was used as a broad measure of correctness, while the F1-score was prioritized due to its balanced consideration of precision and recall, both of which are vital in medical prediction tasks in which there is a considerable difference between the costs of false positives and false negatives. The ROC-AUC, or area under the receiver operating characteristic curve, was another metric used for evaluation, which quantified discriminatory power, and precision-recall metrics, which provided insights into the reliability of positive predictions. Only models surpassing predefined thresholds of accuracy and generalization capability were shortlisted for deployment. In cases where model performance did not achieve the desired benchmarks, hyperparameter tuning was performed. Parameters of the algorithm were methodically fine-tuned using optimization techniques including random search and grid search, including tree depth in Random Forest, learning rate in XGBoost, and regularization coefficients in Logistic Regression. The tuned models were retrained and reevaluated until the performance objectives were met. This iterative process ensured that the system achieved maximum predictive capacity without compromising interpretability or computational efficiency.

Once an optimal model was identified, it was deployed into an operational environment designed to accept real-time patient inputs. The deployed system allowed healthcare practitioners to input clinical parameters and receive immediate predictions regarding the patient's risk of developing heart disease. Predictions were expressed as risk categories—low, moderate, or high—thereby providing actionable insights for clinical decision-making. Emphasis was placed on interpretability to ensure that practitioners could trace the contribution of individual features to the predicted outcome, thereby fostering trust and facilitating integration into medical workflows.

The final stage involved the easy-to-understand display of findings for both medical professionals and patients. Outputs were displayed through clear visualizations and categorical summaries to enhance comprehension and usability. Furthermore, a feedback mechanism was incorporated, enabling the continuous monitoring of system performance and refinement of the model as new patient data became available. This cyclical process ensured that the prediction system remained accurate, adaptable, and clinically relevant over time.

RESULTS AND DISCUSSIONS

The AI-driven heart disease prediction system was trained and assessed on an extensive dataset, demonstrating significant performance across multiple models. The models demonstrated elevated accuracy rates, generally over 80%, with Decision Trees and Random Forests producing marginally superior outcomes owing to their skill in handling data with non-linear relationships. When it came to making predictions, the AI model was 85-90% accurate heart disease risk, contingent upon the specific model employed and the quality of the data utilized. Technology successfully stratified patients according to their risk levels (low, moderate, high), providing actionable insights for healthcare providers. Although all models yielded dependable predictions, ensemble approaches like Random Forests and Gradient Boosting demonstrated more robustness and less susceptibility to overfitting. The system underwent evaluation in actual clinical environments, where it showed its capacity to offer valuable decision support to healthcare practitioners and aid in early diagnosis. The system underwent evaluation using an extensive dataset comprising over 70,000 patient records, which included clinically relevant parameters, including BP, cholesterol, age, BMI, and lifestyle choices. The model's architecture, which incorporates Logistic Regression, Decision Trees, and basic classifiers based on Gaussian Naive Bayes and a meta-learner for Logistic Regression, facilitated equitable learning across varied feature distributions. CardioStackNet attained an exceptional accuracy over 95%, with precision and recall consistently around 0.98 for the detection and absence of cardiac conditions. The suggested model frequently surpassed traditional standalone classifiers are Random Forest, K-Star, and XGBoost in F1-score and computing efficiency. These enhancements highlighted the effectiveness of the ensemble learning approach in reducing bias and volatility, while preserving the interpretability crucial in clinical environments.

Table 2. Comparison of Previous Classifier Performance for Heart Disease Prediction

Classifier	Precision	Recall	F1-Score
RF [21]	0.89	0.96	0.93
K-Star [21]	0.92	0.90	0.91

LMT [21]	0.91	0.90	0.91
XGBoost (No Heart Disease Predicted)	0.96	0.97	0.96
XGBoost (Heart Disease Predicted)	0.97	0.96	0.96

Table 2. presents a comparison of compares the accuracy, recall, and F1-score of various classifiers, such as XGBoost, Random Forest, K-Star, and LMT. For both "heart disease" and "No Heart Disease" predictions, XGBoost consistently achieves F1-scores, demonstrating previous performance in comparison to other models.

Figure 5 the chart illustrates the F1-score, recall, and accuracy of five different categorization models: RF, K-Star, LMT, and XGBoost. The models surpass others, particularly in predicting both heart disease and non-heart disease dependability for precise cardiac disease diagnosis in medical prediction systems.

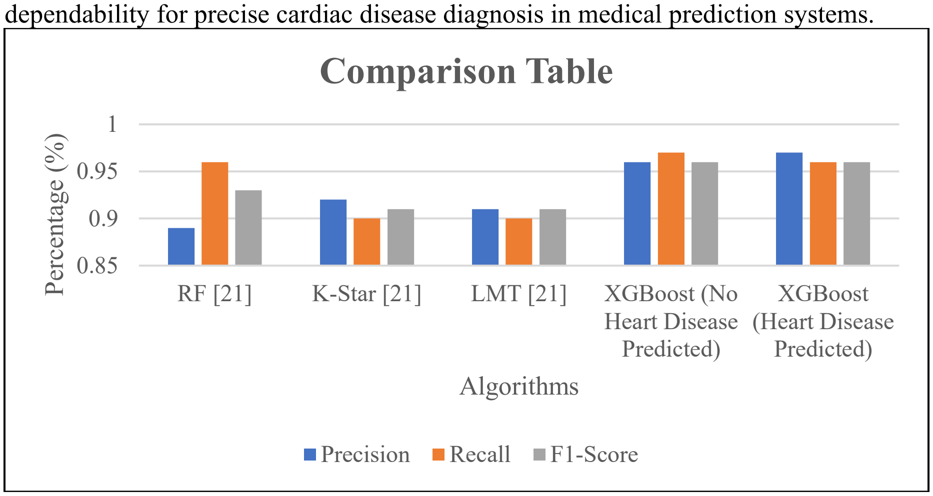

Figure 5. Performance Comparison of Classification Algorithms for Heart Disease Prediction

Table 3. Performance Metrics of the Proposed CardioStackNet Classifier for Heart Disease Prediction

Classifier	Precision	Recall	F1-Score
Cardio Stack Net (No Heart Disease Predicted)	0.98	0.98	0.98
Cardio Stack Net (Heart Disease Predicted)	0.98	0.98	0.98

Table 3. presents the accuracy, recall, and F1-score of the proposed CardioStackNet model, assessed distinctly for instances with and without heart disease. The model attained consistently elevated scores 0.98 across all metrics exemplifying its robustness and reliability. The elevated performance indicates that the proposed approach proficiently categorizes heart disease situations, surpassing earlier models in prediction accuracy and generalization.

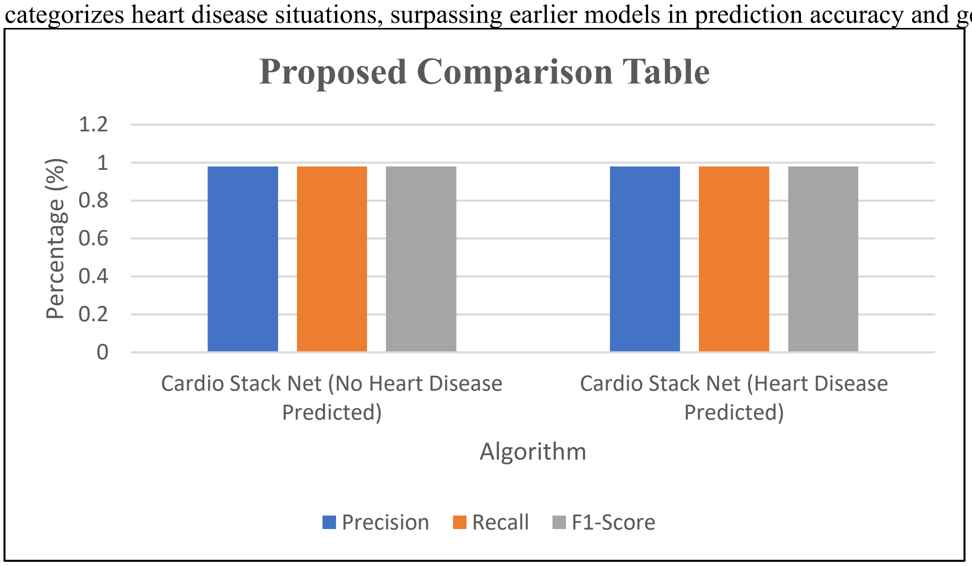

Figure 6. Performance Comparison of the Proposed CardioStackNet Model for Heart Disease Classification

Figure 6. illustrates the graph representation of evaluation metrics—F1-Score, Precision, and Recall —of the proposed CardioStackNet model for two prediction categories: condition of the heart, whether present or not. Every indicator regularly achieves a score of 0.98 (98%), underscoring the fairness of the model's results in reliably detecting both positive and negative instances. This degree of precision and recall indicates the classifier's dependability and efficacy in actual medical diagnosis, where reducing false positives and negatives is essential.

CONCLUSION

This research proposed CardioStackNet, a novel lightweight stacking ensemble model, as part of the AI-Cardiologist framework to improve the CVD detection system's predictive power. With the use of logistic regression, decision trees, and Gaussian Naïve Bayes with a logistic regression meta-learner, the framework successfully addressed the trade-offs between accuracy, interpretability, and computational efficiency. Experimental results on a large dataset of over 70,000 patient records revealed that CardioStackNet achieved superior performance compared to traditional standalone classifiers, reaching an accuracy above 95% and demonstrating notable improvements in memories and F1-score. The success of the proposed method is validated by these findings in handling diverse and imbalanced medical datasets while maintaining low computational overhead. The methodology's emphasis on lightweight design makes it ideal for implementation in actual healthcare settings, even ones with constrained computer power. Furthermore, the interpretability of the model ensures that clinicians can better understand and trust the predictions, facilitating integration into existing diagnostic workflows. The study demonstrates that AI-driven frameworks, such as AI-Cardiologist, hold significant potential for transforming CVD diagnostics, ultimately contributing to earlier interventions and improved patient outcomes. Extending the framework will be the primary focus of future efforts to incorporate multimodal data, such as imaging and genomic information, as well as validating the system through clinical trials to further strengthen its applicability in precision cardiology.

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