Hybridizing Wolf Search Algorithm With Xgboost Model For Accurate Identification Of Cardiac Disorders

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Abstract. *Rapid and accurate diagnosis is necessary to treat heart disorders, a global health issue. Medical diagnosis tasks have shown promising results with machine learning, notably ensemble algorithms like XGBoost. Still, you must adjust these models' hyperparameters to maximize their performance. This research combines the Wolf Search Algorithm (WSA) with XGBoost to improve heart disease identification. We apply WSA to optimize XGBoost classifier hyperparameters like learning rate, tree depth, and regularization. A big collection of diagnostic and clinical data from patients with various cardiac conditions was used for our tests. Preprocessing addressed missing val- ues and ensured uniform scaling. Our hybrid methodology was tested using rigorous cross-validation methods to determine AUC-ROC, sensitivity, specificity, and accuracy. A combo of WSA and XG- Boost enhances heart issue diagnosis accuracy compared to conventional parameter tuning methods. The poposed model gained 0.973 accuracy level, 0.97 precision value, 0.89 recall value with 0.93 f1-score. Several performance indicators show the upgraded XGBoost model can discriminate car- diac conditions. Additional insights on model interpretability and feature importance for diagnostic decision-making are offered. We found that XGBoost and swarm intelligence algorithms like WSA can increase heart disease diagnosis reliability and accuracy. Implementing the provided methods in clinical settings may improve healthcare outcomes and patient management.*

Key words. *Wolf Search Algorithm (WSA); XGBoost; Hyperparameter Tuning; Cardiac Dis- orders; Heart Diseases; Diagnosis*

1. Introduction. Cardiac problems impact the heart, one of the body's most vital organs. Global healthcare systems face significant problems from cardiac abnormalities, which can range from congenital defects to acquired diseases, in terms of frequency, morbidity, and mortality. Understanding these illnesses' complicated causes can improve prevention, diagnosis, and therapy. To maintain cellular metabolism, the heart pumps oxygen-rich blood throughout the body as a complex pump. When this complicated mechanism is disturbed, a chain reaction of physiological abnormalities can cause many heart diseases. Many diseases have systemic implications that diminish quality of life and health, as well as cardiovascular health. Even while therapeutic approaches and technology developments have improved cardiac care, they nevertheless burden healthcare systems, families, and individuals worldwide. Is- chemic heart disease, arrhythmias, heart failure, congenital heart defects, and valve anomalies require customized diagnosis and treatment (Baier et al., 2006; Khoo et al., 2013; Santana et al., 2012).

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Sedentary lifestyles, poor diets, aging populations, and increased incidence of risk factors like hypertension, diabetes, and obesity are also contributing to heart illness. Thus, thorough prevention, early diagnosis, and appropriate care must be implemented immediately to reduce the public health impact of heart disorders. Many disorders and ailments can impair the heart's blood-pumping function, threatening its health. Various cardiac problems can occur from infancy to adult- hood. These illnesses have different symptoms, etiology, diagnostic procedures, and therapies. This section introduces cardiac issues, their intricacies, and the importance of early diagnosis and treatment (Dar et al., 2015; Le et al., 2013).

1.1. Types of Cardiac Disorders.

1.1.1. Coronary Artery Disease (CAD). The most common cardiac disease is coronary artery disease (CAD), which occurs when plaque narrows or stops the arteries. The symptoms include angina, difficulty breathing, and drowsiness. ECG, EKG, stress testing, angiography, and cardiac catheterization are common diagnostic procedures (Lanata et al., 2015). Treatment may include medications, lifestyle changes, angioplasty, or bypass surgery.

1.1.2. Heart Failure. Heart failure occurs when the heart cannot pump blood properly, causing fluid to build in tissues, including the lungs. The symptoms include trouble breathing, drowsiness, leg edema, and a beating heart. Cardiovascular imaging, BNP testing, chest X-rays, MRI, and CT are used for diagnosis. Treatment includes diuretics, ACE inhibitors, behavioral modifications, and, in extreme cases, a heart transplant.

1.1.3. Arrhythmias. Arrhythmias can be fast (tachycardia) or slow. Symp- toms include palpitations, fainting, lightheadedness, and chest pain. Electrophysiology, Holter monitoring, event recording, and electrocardiograms are diagnostic tools. Pacemakers, defibrillators, and ablation are treatment possibilities.

1.1.4. Valvular Heart Disease. Blood flow in the heart is impaired by valvular heart disease, which is caused by valve injury or failure. Symptoms include palpitations, tiredness, breathing difficulties, and chest pain. Echocardiography, cardiac catheterization, and imaging are utilized to diagnose. Treatment may include medication, surgical valve repair or replacement, or TAVR.

1.1.5. Cardiomyopathy. Anatomical and functional issues result from cardiomyopathy. Symptoms include breathlessness, tiredness, edema, and irregular heart- beats. Diagnostics include ultrasound, MRI, CT, genetic tests, and biopsies. Medical, behavioral, or sophisticated treatments including implanted devices or heart trans- plants may treat cardiomyopathy.

1.1.6. Risk Factors and Prevention. Common risk factors include hyper- tension, diabetes, obesity, smoking, lack of exercise, high cholesterol, and a family history of heart disease. Maintaining a healthy weight, exercising, eating a balanced diet, not smoking, and managing stress reduces the risk of cardiovascular disease. Cardiac disorders are global health issues because they kill and disable people world-wide. Early detection, accurate diagnosis, and proper intervention are essential for managing chronic disorders and improving patient outcomes. Medical technology and research continuously improve our understanding of cardiac issues. This allows new treatment and prevention methods. We can improve heart disease control and save lives by increasing knowledge, promoting healthy lifestyles, and fighting for fair healthcare access.

1.2 Problem formulation. Heart disease identification is crucial for many reasons. First, cardiac issues are a major cause of illness and death worldwide (Miao et al., 2019; Mishra et al., 2017; Tara et al., 2018). If diagnosed early, appropriate therapy can decrease disease progression and improve patient outcomes. Many heart disorders are asymptomatic or have ambiguous symptoms, making screening and diagnosis difficult without the correct instruments. Early identification allows doctors to start treatment before significant conditions like heart failure, arrhythmias, or myocardial infarction occur. When heart disease risk factors are identified, medication, lifestyle adjustments, and cardiac rehabilitation programs can be more easily administered. This prophylactic technique reduces the cost of treating serious cardiac issues and improves patients' quality of life (Deshwal et al., 2023; Rustagi, T et al., 2023).

1.2.1. Methods of Identification. Doctors utilize non-invasive screening tests, high-tech imaging, and invasive procedures to diagnose cardiac issues. Popular methods include:

- Physical Examination: A thorough physical examination includes peripheral pulse measurement, vital sign assessment, and heart sound auscultation to determine cardiac function and potential issues.
- Electrocardiography (ECG): The non-invasive electrocardiogram (ECG) records heart electrical activity. It detects structural cardiac abnormalities, myocardial ischemia, conduction irregularities, and arrhythmias.
- Echocardiography: Echocardiography shows the heart's architecture and function live using ultrasonic pulses. It checks heart chamber size, motion, and abnormalities like congenital heart defects, cardiomyopathies, and valve is- sues.
- Cardiac Imaging: Nuclear imaging, CT angiography, MRI, and other methods disclose the heart's architecture and function in detail.
- Cardiac Catheterization: Through invasive treatments like coronary angiography and cardiac catheterization, coronary arteries can be visualized, heart chamber pressures monitored, and tissue samples collected for further study.

Even with advanced diagnostic tools, heart abnormalities are difficult to detect:

- Access to Healthcare: In poor countries with little healthcare, cardiac issues may go undiagnosed and untreated for longer.
- Cost and Affordability: Many cardiac evaluation tests and treatments are too expensive for low- income or uninsured people.
- Interpretation and Expertise: Diagnostic test interpretation requires expertise and training. Lack of training might cause doctors to misunderstand results and delay diagnosis.
- Patient Compliance: Patients must follow screening and follow-up instructions to detect cardiac problems quickly. Patients may struggle to follow doctors' advice due to fear, denial, or ignorance.
- False Positives and Negatives: Diagnostic tests might give inaccurate results, leading to unnecessary examinations or missed diagnosis. Diagnostic testing reliability and accuracy must be improved to detect heart disorders (Chang et al., 2019; Guo et al., 2020)

Early cardiac diagnosis allows for rapid treatment, improving patient outcomes. Using non-invasive tests, imaging, clinical evaluation, and invasive procedures, doctors can diagnose many cardiac illnesses. Access to healthcare, economic limitations, and interpreting skills must be addressed to improve heart disease identification and re- duce global burden. Public health measures, healthcare infrastructure expansion, and continued medical education are needed to solve these issues and improve cardiac care worldwide (Al-Absi et al., 2021; Deviaene et al., 2020; Rahman Khan et al., 2020).

1.3. Research Contributions. Hybridizing the Wolf Search technique (WSA) with XGBoost, a famous gradient boosting technique, to accurately identify cardiac diseases can lead to various research advances:

- Combining the WSA's global search and XGBoost's complicated data pattern capture can improve cardiac problem diagnosis in this work.
- In this paper, WSA swiftly searches the search space, while XGBoost learns from data to produce accurate predictions.
- Using XGBoost's feature importance, the hybrid technique has chosen fea- tures effectively.
- In this paper, the authors focus on heart problem causes by finding the most important features, enhancing accuracy and interpretability and achieved the accuracy level 97.6/
- While feature significance gives XGBoost some interpretability, hybridizing it with WSA can improve it. WSA's optimization process helps clinicians comprehend cardiac diseases causes by highlighting key elements.

WSA's population-based search improves model scalability and efficiency, especially for large datasets. The hybrid technique handles high-dimensional and large-scale datasets quickly by exploring the search space, making it ideal for real-world applications.

The complete research is organized as follows. Section two reviews and com- pares existing research in heart disease prediction. Section three presents materials and methods, covering the details of existing processes and architecture, features of a proposed hybrid model, and dataset description. Section four covers the practical information, simulation parameters, data pre-processing, simulation results, and the results and discussion to justify the research. The last section, five, covers the conclusion of the present heart disease prediction work and suggests its limitations and future direction.

2. Related Work. Baier et al. (2006) recorded 41 healthy women, 34 preeclampsia women, and 15 pregnancy-induced hypertension women after 30 weeks. With fifteen hidden states, RR-based HMMs classified blood pressure fluctuations well, but HMMs. The unique pathophysiological autonomous regulation of preeclampsia and pregnancy-induced hypertension implies different causes.

Santana et al. (2012) developed, tested, and implemented CUiiDARTE's health informatics strategy. The goals were to 1) encourage subclinical atherosclerosis screenings, 2) create a national database for noninvasively collected data, 3) create a biomathematical model that incorporates arterial structure and function into conventional cardiovascular risk assessment, 4) provide specialists with an in-depth report comparing patient data to healthy population reference data, and 5) provide patients with an equivalent report. This article describes the main CUiiDARTE health informatics development characteristics.

Dar et al. (2015) provide a systematic strategy to person identification using electrocardiograms (ECGs) in various cardiac conditions through ECG preprocessing, feature extraction, feature reduction, and classifier performance. ECG segmentation uses R-peak detection, although it does not require fiducial detection or computational complexity. Using discrete wavelet transform, we combine cardiac cycle and HRV characteristics to extract features. Best first search reduces features and Random Forests classifies. The system is evaluated using three publicly available datasets. Our accuracy was 95.85% with a FAR of

4.15% and a FRR of 0.1%. On datasets based on normal populations, the method scores 100% with the NSRDB database and 83.88% with the harder ECG-ID database. Mishra et al. (2017) provide wavelet domain cardiac sound analysis for automated heart disease identification. Using wavelet domain modification, heart sounds from normal and pathological individuals can be distinguished. Automatic cardiac disease screening uses machine learning to identify discriminatory features from heart sound wavelet coefficients. Tests on a large heart sound database showed positive results for the suggested cardiac disease screening technique. Experimental results reveal that the suggested technique accurately diagnosed cardiac diseases.

Tara et al. (2018) developed MATLAB-based Graphical User Interfaces to automatically detect heartbeat infections. An individual with this ailment has a shorter RR interval than normal. Affected heart beats had a lower LF/HF ratio but in- creased heart rate, kurtosis, and skewness. A MATLAB- based GUI platform is used to evaluate the suggested categorization algorithm against medical records. The result matches the doctor's evaluation and benefits the clinic. A new technology can swiftly and reliably determine cardiac health.

Chang et al. (2019) use the recently proposed XGBSVM hybrid model to predict hypertensive heart disease in three years. The latest research showed that hypertensive people can reduce their emotional, physical, and financial burden by identifying their risk of hypertensive heart disease within three years and receiving concentrated preventative treatment. This study shows that biological machine learning is feasible and theoretically sound.

Recursion enhanced random forest with an improved linear model was suggested by Guo et al. (2020) to diagnose cardiac issues. This study uses machine learning to discover key cardiovascular disease prediction factors. The prediction model uses several well-known classification methods and feature combinations. The cardiac problem prediction model improves performance. This research reveals cardiovascular disease causes. Data analysis using the IoMT platform compared pertinent factors. This shows coronary artery disease is more common among the elderly. High blood pressure also spreads this disease. To that aim, preventative measures are needed, and diabetes adds another component to the mix for predicting coronary artery disease.

Rahman Khan et al. (2020) classified five ECG arrhythmic signals using the Physionet MIT-BIH Arrhythmia Dataset. Artificial Neural Networks have considerably improved ECG signal categorization. We recommend a CNN to classify ECG data. Our results show that the projected CNN model classifies arrhythmia with 95.2% accuracy. Average recall is 95.40% and precision is 95.2% for the suggested model. This method detects cardiac rhythm disorders early.

ML models trained on known CVD risk factors performed worse than those trained on multimodal datasets, underscoring the need for additional clinical indicators in CVD diagnosis schemes (Al-Absi et al., 2021). Bioimpedance and physio- clinical parameters were the best at distinguishing the two groups in the QBB multimodal dataset ablation study, regardless of age or gender. The ML model with the recommended novel components outperforms the one utilizing conventional CVD risk variables. Clinical examination of putative risk factors and comorbidities in CVD is needed to better understand their importance.

Pashikanti et al. (2022) used proven intelligent system development approaches fuzzy systems and neural networks (NNs). This study develops and tests a 3D-CNN for 2-lead ECG signal binary classification (normal/arrhythmia) using the MIT-BIH dataset. Fuzzy Inference System underpins the network. F- score, recall, precision, specificity, sensitivity, and accuracy show categorization results. We test the approach in MATLAB and evaluate it.

Joy et al. (2023) found that deep learning-based convolutional neural networks (CNNs) improve cardiac illness diagnosis and management. ECG analysis requires AI, which this review explains. Public and private access to extensive clinical ECG data has enabled the management of many cardiac and non-cardiac illnesses.

Mahmud et al. (2023) evaluated 2D heartbeat pictures. Our ECG signal classification accuracy is 0.94 and our ECG image data accuracy is 0.93 using ensemble methods to integrate model predictions. AI can replace ECG interpreters in modern medicine to improve patient care. This review examines the potential, limitations, and hazards of clinical and research electrocardiogram (ECG) testing for cardiac problems.

Venkatesan et al.(2023) use feature extraction and ECG signal preprocessing to detect cardiac arrhythmias and quantify CHD risk. This paper shows how to use an SVM classifier to detect cardiac arrhythmias after ECG signal preprocessing. Arrhythmic beat classification is the next stage in detecting problems in preprocessed ECG signals. SVM classification-based technique separates extracted R-peaks from ECG data into normal and arrhythmic risk patients to find problems. The K-Nearest Neighbor (KNN) classifier exceeds all others with 97.5 In 2023, Bhan et al. will segment MRI scan images using Vanilla-CNN, FCNN, and ResNet to locate the RV. This helps detect heart irregularities and CVD. We evaluate the suggested algorithms using industry-standard performance criteria to determine their efficacy and feasibility. All CNN flavors, including Vanilla, FCNN, and ResNet, can accurately segment pictures to identify CVDs, according to DL algorithms (Lilhore et al., 2024).

Mondal et al. (2024) introduce a dual-stage stacked machine learning-based cardiac risk prediction model. Five ML classifiers are used to build the initial prediction model from 1190 patients from five sources with eleven important characteristics. Classifiers undergo 10 rounds of cross-validation to ensure robustness and generalizability. Hyperparameter tweaking with Randomized Search CV and Grid Search CV optimizes model performance. Several methods are used to find the best estimate values. Stacking ensemble refines the best models like Decision Tree, Random Forest, and Extreme Gradient Boost. Stacking the strengths of all three models yields 96% accuracy, 0.98 recall, and 0.96 ROC-AUC. A false-negative rate of less than 1% indicates that the model is not overfitted and has great accuracy.

Hudson et al. (2024) reanalyzed 232 cross-sectional cohort individuals. Adolescent body image difficulties, particularly muscular dysmorphia, were the strongest predictors. The model's stability and repeatability are verified using a 1000-occurrence dataset. Under the same testing settings, the model consistently achieves 96.88% ac- curacy. Table 2.1 demonstrates the summary of existing works as below.

2.1. Research Gaps. To identify knowledge gaps in heart disease diagnosis, one must be familiar with cardiology's current diagnostic landscape. The following areas may lack research:

- Developing non-invasive heart screening methods to identify and treat high- risk patients.
- Enhancing echocardiography, MRI, and CT scan accuracy and efficiency with AI and machine learning algorithms.
- Standardization aims to create reliable and consistent heart disease diagnostic standards

across healthcare settings and populations. These criteria must also be tested in different clinical contexts and with different patients.

- Finding novel biomarkers for arrhythmias, coronary artery disease, and heart failure to improve diagnosis and prognosis.
- Personalized diagnostic methods that account for genetics, lifestyle, and co-morbidities improve diagnosis accuracy and treatment strategies.
- Investigating how telemedicine and remote monitoring systems can help dis- advantaged or distant areas detect and cure heart diseases.

Authors	Methods	Dataset	Outcomes	Limitations
(Santana et al., 2012)	Random Forest CUii	DARTE Dataset	81.25% Accuracy	Less Accurate
(Le et al., 2013)	Octant network	PTB database of	88% Accuracy	Less Accurate
(Chang et al., 2019)	SVM Model	LARMSBP dataset	91.70% Accuracy	Outfitting issues
(Deviaene et al., 2020)	Multilevel Interval Coded Scoring	Leuven dataset	AUC of 93.5%	Lack of patient follow-up
(Tripathi et al., 2022)	Linear discriminant analysis	PhysioNet dataset	96.0% Accuracy	Not hypertunned
(Kumar et al., 2023)	Navie Bayes	UCI dataset	90.66% Accuracy	Slower than large datasets
(Mohi Uddin et al., 2023)	Gradient boost	ENSEMBL database	92.16% Accuracy	Outfitting issues
(Jiang et al., 2024)	Facial Expressions and Visual Patterns	“WIDER” face dataset	AUROCs of 0.72–0.82	Less Accurate
(Vahab et al., 2024)	CNN and Random Forest	ENSEMBL database	AUC 0.94	Outfitting issues
(Nyström et al., 2024)	Residual neural networks	collected from 19,499 consecutive	0.76 AUC	Less accurate

TABLE 2.1
Review of existing works

- To ensure fair healthcare for all cardiac patients, access to advanced diagnostic procedures and technologies must be addressed, especially in low-resource settings.
- Improving long-term monitoring for chronic heart disease patients to better track their condition, therapy, and outcomes.

- Encourage radiologists, geneticists, and cardiologists to collaborate to enhance difficult heart disease diagnosis using their distinct knowledge and experiences.
- Research that prioritizes patients' perspectives and outcomes ensures diagnostic approaches consider their values, preferences, and quality of life.

Researchers and clinicians can fill these cardiac diagnostics knowledge gaps to improve patient care by diagnosing heart issues earlier and more accurately.

3. Material and Method.

3.1. **`Dataset**. A target variable indicating heart disease presence or absence is frequently included in this dataset, along with many patient and health condition attributes. These datasets are used in statistical and machine learning analysis for risk assessment, classification, and predictive modelling (Rapp et al., 2022; Tenekeci Isik, 2022). Here are typical heart disease dataset attributes with help of the heat map and histogram below: Fig 3.1 demonstrates the heat map.

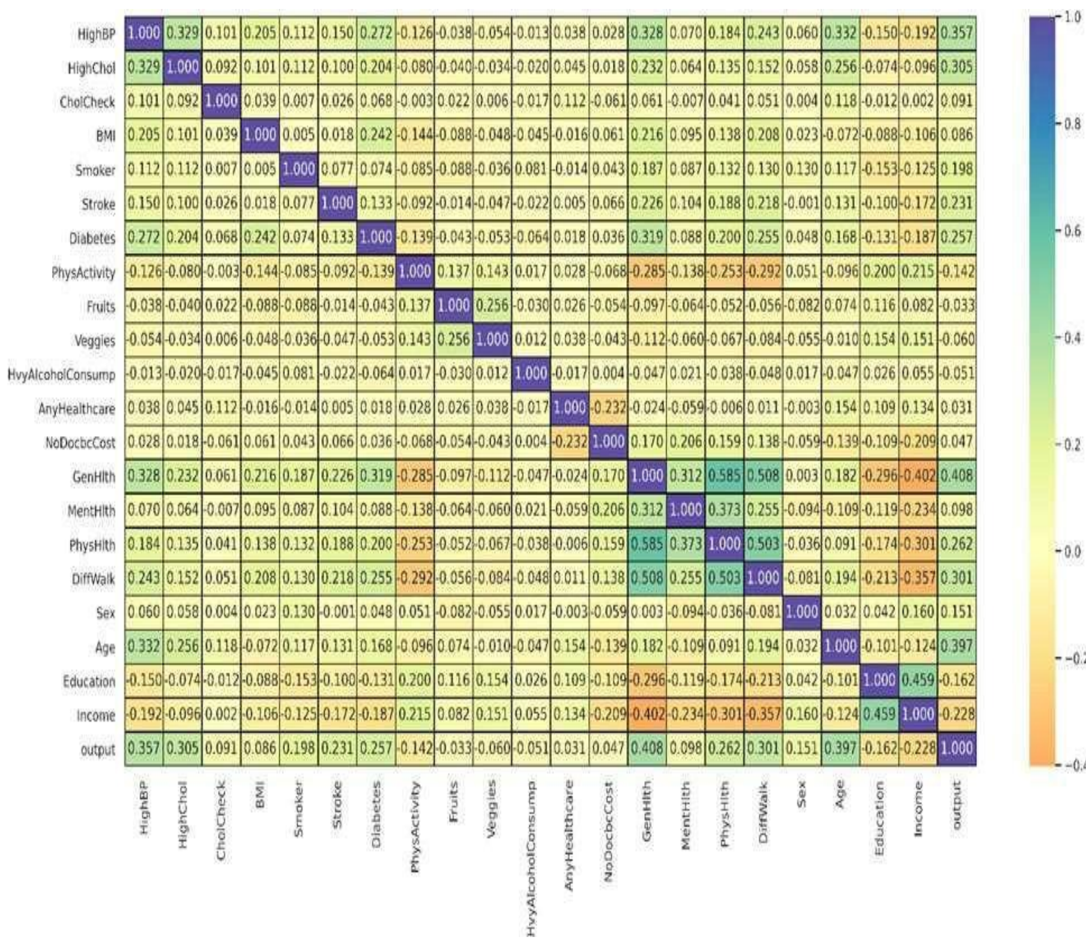

FIG. 3.1. *Heat map*

Fig 3.2 demonstrates a histogram for the Heart disease Dataset.

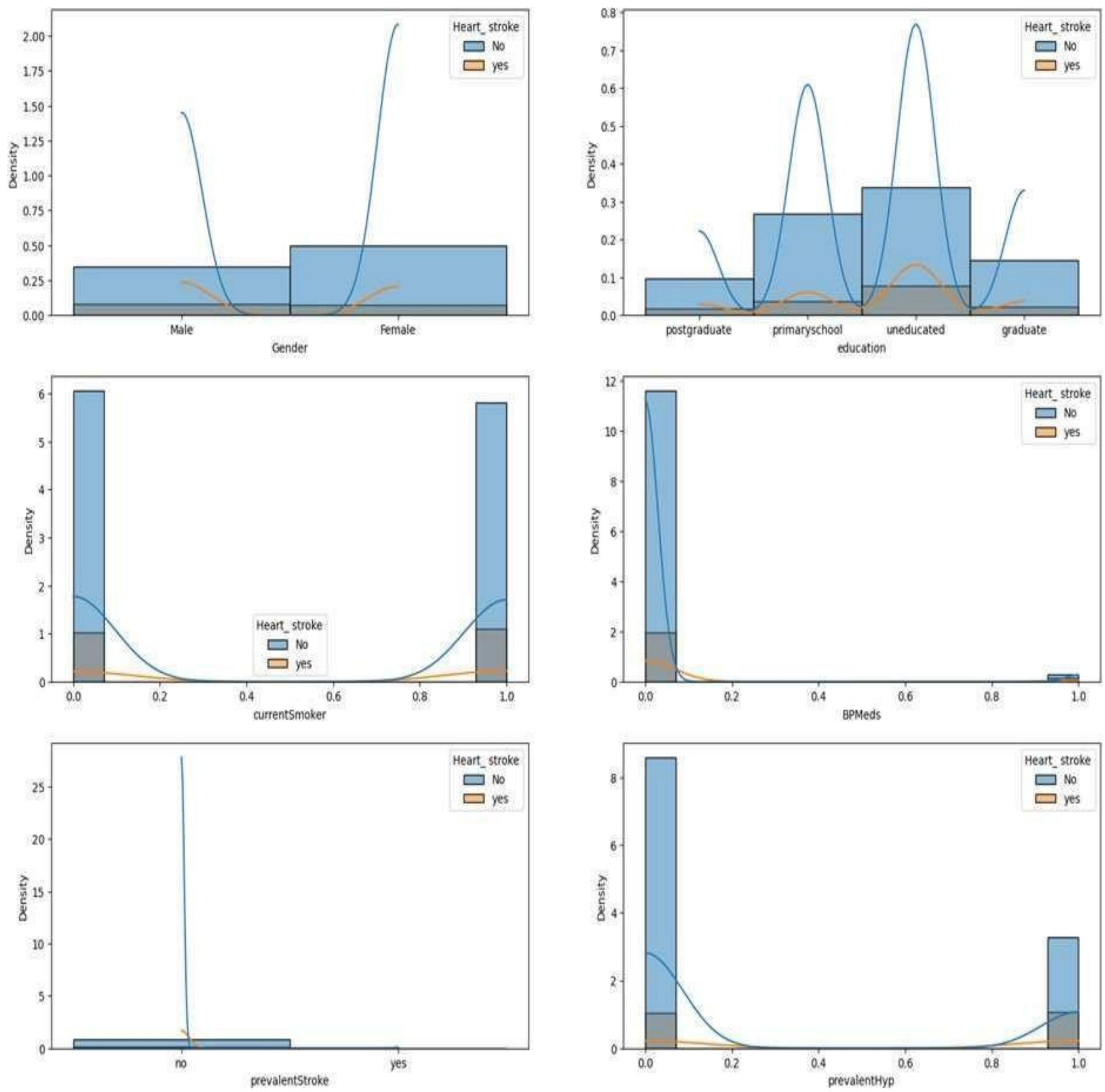

Fig. 3.2. Histogram

The authors began by finding missing values in the dataset. Using mean imputation, writers filled numerical feature gaps. Because feature values can vary significantly, normalisation was necessary to ensure that all features had an equal impact on the model. With Min-Max Scaling, writers assigned zero to one to each characteristic. This was especially important for features with varying scales to prevent smaller features from overshadowing larger ones during model training. To increase data quality and model performance, the authors cleansed it several times. Outliers were discovered and removed using the interquartile range (IQR) method to avoid biassed model predictions. Authors found and fixed data errors, including duplicate entries. The authors employed feature engineering to improve model predictions: Interaction terms between essential features were created to account for non-linear connections. These preprocessing steps were crucial in preparing the dataset for the subsequent modeling phase, ensuring robust and reliable predictions of heating and cooling load requirements in building energy efficiency.

Our methodology requires outlier identification before employing the hybrid Wolf

Search Algorithm (WSA) and XGBoost model to ensure data integrity and reliability. Medical data anomalies, especially outliers, might impair machine learning algorithms. We performed an exploratory data analysis (EDA) to understand the dataset's distribution and features. To find outliers, histograms, box plots, and scatter plots were used. The Z-score and Interquartile Range (IQR) methods were used to find data abnormalities. Outliers were data points with Z-scores above or below 3. The Z-score measures a data point's standard deviation from the mean. Outliers were data points below the first quartile minus 1.5 times the interquartile range (IQR) or above the third quartile plus 1.5 times the IQR.

3.2 Methods. The XGBoost algorithm is a formidable contender in the domain of machine learning, where prediction accuracy and efficiency reign supreme. Tianqi Chen developed the eXtreme Gradient Boosting (XGBoost) algorithm, which has garnered significant acclaim for its exceptional performance across numerous do- mains. XGBoost iteratively mitigates a pre-established loss function and attempts to rectify errors introduced by preceding models through the continuous addition of new models to the ensemble. Unique to XGBoost is its emphasis on optimizing models for both computational speed and accuracy. To achieve its remarkable efficiency while preserving its predictive capability, XGBoost implements distinctive methodologies such as tree pruning, parallel and distributed computation, and cache- aware access patterns (Blanchard et al., 2022; Dai et al., 2022; Pashikanti et al., 2022; Tripathi et al., 2022). A loss term quantifies prediction errors, and a regularization term regulates model complexity; XGBoost optimizes this individualized objective function. XGBoost is capable of being modified to accommodate various learning activities and assessment criteria due to its adaptability. XGBoost employs a dual- pronounce L1 (Lasso) and L2 (Ridge) regularization to prevent overfitting. This approach strikes an equilibrium between the intricacy of the model and the accuracy of the data fitting. XGBoost employs the gradients and Hessians, which are the initial and final derivatives of the loss function in relation to the anticipated scores, to guide the training procedure in an efficient manner. XGBoost provides insights on feature relevance to aid in feature selection and interpretation, enabling users to identify the most influential variables within their datasets. XGBoost leverages parallel and distributed computation frame- works to streamline the training process on multicore CPUs and distributed clusters, thereby enabling the model to effectively manage enormous datasets (Behera et al., 2022).

XGBoost is applicable to a wide range of machine learning tasks, including but not limited to recommendation systems, ranking, classification, and regression, due to its adaptable nature. Due to its exceptional performance and robustness, it has become a standard in data science competitions. Numerous domains, including financial forecasting, customer attrition prediction, anomaly detection, e, depend on predictive models powered by XGBoost. Additionally, XGBoost is pervasive in industrial contexts. XGBoost represents a paradigm shift in the field of machine learning, offering state-of-the-art capabilities in predictive modeling through the seamless integration of algorithmic sophistication and computational efficiency. It is utilized by data scientists and machine learning practitioners worldwide due to its extensive impact in academia, industry, and competitions. XGBoost is at the forefront of ma- chine learning's dynamic domain, facilitating innovations and providing solutions to challenging real-world issues (Joy et al., 2023; Kumar et al., 2023; Zhang et al., 2022). By repeatedly partitioning the data according to characteristics that reduce the loss function, GBoost builds trees in a greedy fashion. The goal of selecting the splits is to maximize a gain metric that is computed with the help of the gradients and Hessians.

Algorithm 1

Step 1: Start with an initial prediction yi, often set as the mean of the target variable for regression tasks or the log odds for binary classification tasks.

Step 2: Repeat this step for m=1, 2,. . . ,M, where M is the total number of trees (iterations):

Compute the negative gradient of the loss function with respect to the current prediction in Eq. 1 for each training sample

$$((y_i - y_(i + 1)))/(y_i)(1)$$

Fit a regression tree (weak learner) to the negative gradients obtained in the previous step. The tree is typically constrained by its depth, number of nodes, and other hyperparameters to prevent overfitting.

Determine the optimal tree structure (splits) by recursively partitioning the feature space to minimize the loss function. This involves finding the split points that maximize the gain in predictive performance.

Update the predictions by adding the predictions of the newly fitted tree to the previous predictions. This update is scaled by a learning rate (shrinkage parameter) to control the contribution of each tree to the ensemble.

Step 3: After constructing all trees, the final prediction is obtained by summing the predictions from all trees in the ensemble.

Step 4: Regularization techniques like shrinkage (learning rate), tree depth, and leaf node weights are used to control the complexity of the ensemble and prevent overfitting.

Step 5: To prevent overfitting, a validation set is often used to monitor the performance of the model during training. Training stops when the performance on the validation set fails to improve for a specified number of iterations.

Step 6: Throughout the training process, the algorithm optimizes a predefined objective function, which is typically a combination of a loss function and regularization terms.

The XGBoost algorithm's hyperparameters affect learning rate, regularization, tree construction, model complexity, and more (Mahmud et al., 2023). Other general categories for these factors include:

Tree Booster parameters:

- The learning rate determines the gradient boosting step size per iteration. Though it takes more rounds, slower-learning models are more resilient.

- Max d*epth is the ensemble's maximum decision tree depth.*

Higher values may lead to more complex, overfitting models.

- Standardisation parameter gamma controls the minimum loss reduction needed to split a leaf tree node.
- L2 regularization term describe the impact of magnitude impacts leaf weights.
- Alpha controls L1 regularization strength, promoting feature sparsity.

Data Sampling Options includes Subsample chooses a percentage of training data to randomly select at each boosting step. By adding unpredictability, lower numbers may prevent overfitting.

Grid Search and Random Search can randomly sample the hyperparameter space or search a grid of hyperparameter combinations to find the optimum configuration. Bayesian Optimization iteratively explores hyperparameter space using probabilistic models to find performance-boosting regions. Cross-validation prevents overfitting and improves performance estimates by assessing the model across many hyperparameter settings (Bhan et al., 2023; Mohi Uddin et al., 2023; Venkatesan et al., 2023). Importantly, XGBoost hyperparameters affect model behavior and performance. Understanding each hyperparameter and tuning techniques is essential to creating ac- curate and robust prediction models. Machine learning practitioners must master hyperparameter tuning to maximize the potential of XGBoost and other sophisticated algorithms as they explore new datasets and perform more tasks. Like wolves, it hunts in packs and expands its territory. Authors define XGBoost hyperparameter space. This space typically contains learning rate, maximum tree depth, number of trees (boosting rounds), subsample ratio, column subsampling ratio, regularization parameters (gamma and alpha), and subsample ratio. The authors evaluate the XG- Boost model's output using a cardiac disease dataset. The authors trained a pack of wolves, each representing a hyperparameter solution for the classification task. The authors generate the fitness values of the alpha, beta, and delta wolves by training an XGBoost model with the right hyperparameters and utilizing the objective function to compute its validation set performance. We believe these wolves are the population's best option. After that, the authors adjust each wolf's position while staying inside the hyperparameter space (Sai Kumar et al., 2023; Sarvani et al., 2024; Weiss et al., 2023).

Machine learning requires regularization to improve model generalization and avoid overfitting. L1 Regularization (Lasso) penalizes the model proportionally to co- efficient magnitude to simplify it. This penalty selects features by zeroing coefficients. L2 Regularization (Ridge) penalizes according to the square of coefficient magnitude. This decreases huge coefficients without deleting them; the model preserves all properties. Elastic Net blends L1 and L2 regularization with a penalty that balances their benefits, making it ideal for datasets with linked features. Dropout is a typical neural network training method that randomly removes neurons to prevent neuronal co-adaptation overfitting. Finally, early halting terminates training when validation set performance stops improving to prevent model overfitting. Each regularization method has pros and cons, therefore choosing one relies on the model and dataset.

Next, set a termination criterion like a maximum number of iterations, computation time, or a satisfactory solution, and then adjust the algorithm's exploration and exploitation parameters to balance searching new hyperparameter space and refining promising regions. If termination is met, use the fittest wolf to tune hyperparameters. Follow these steps to hyperparameter tune XGBoost models using the Wolf Search

Algorithm and find cardiac issues. This strategy improves the model's real-world cardiac irregularity detection.

Algorithm 2

Start

1. Initialize:

- Initialize population of wolves with random positions
- Evaluate fitness of each wolf in the population
- Set parameters: population *size, maxiterations, alpha, beta, delta* *(1)*

2. Repeat for max_*iterations* :

2.1 Update position and fitness of each wolf:

X_new=X_old+β*ΔX (2)

Where Xnew Xold represents existing and old positions,

β represents random vector and

Δ is difference

For each wolf in population:

2.1.1 Select alpha, beta, and delta positions (best, second best, and third best)

2.1.2 Update position of the current wolf based on alpha, beta, an delta positions

$$D_{a}lpa = |C.D_{a}lpha + D_{w}olf| \quad (3)$$

$$D_{b}eta = |C.D_{b}eta + D_{w}olf| \quad (4)$$

$$D_{g}amma = |C.D_{g}amma + D_{w}olf| \quad (5)$$

Where Dalpa , Dbeta , Dgamma represents distance between existing old positions, C represents random coefficient and D_{w}*olfis Current position*

2.1.3 Ensure the new position is within the search space boundaries

2.1.4 Evaluate fitness of the new position

2.2 Update alpha, beta, and delta positions:

For each wolf in population:

2.2.1 Update alpha, beta, and delta positions if necessary based on fitness

2.3 Update exploration and exploitation rates:

2.3.1 Update alpha, beta, and delta exploration and exploitation rates based on their fitness

3. Output:

- Return the best solution found

End

Fig 3.3 demonstrates the flow chart of the proposed methodology below.

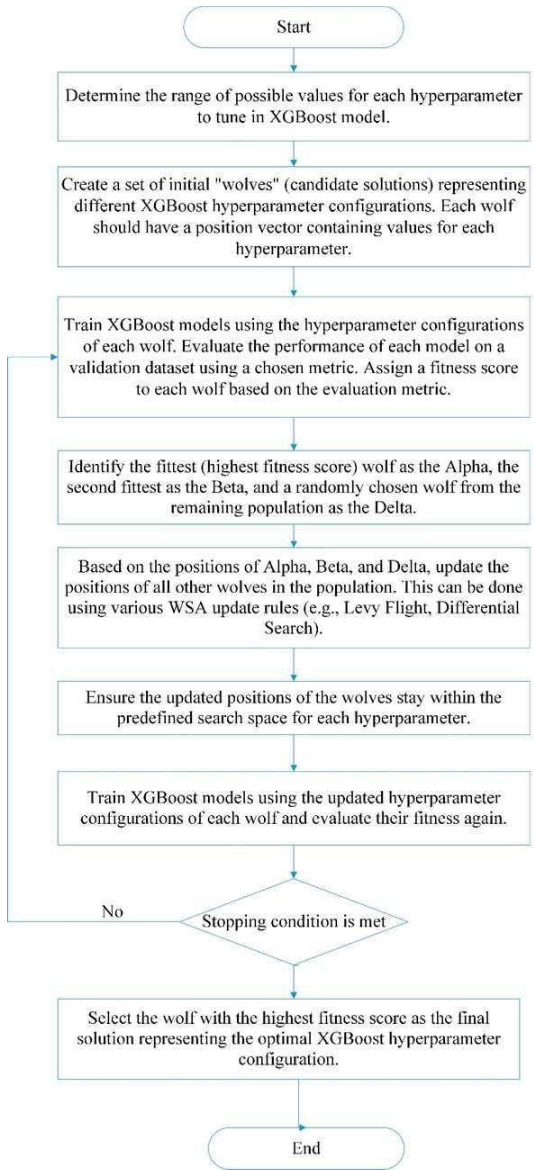

FIG. 3.3. *Flow chart of proposed methodology*

Alpha, Beta, and Gamma are key Wolf Search Algorithm (WSA) variables that affect search behaviour and convergence. Alpha represents the pack's dominant wolf's power. It measures how much the dominant wolf affects subordinate wolf locomotion. The dominant wolf influences the other wolves' direction and distance during the search if Alpha is high. The second-ranking wolf's effect is determined by beta. The second-best wolf's impact on the search method is balanced by this parameter. Beta can be adjusted to calibrate the algorithm's exploration and exploitation. The pack's third-skilled wolf has Gamma. The word alludes to the third-ranked wolf's search contribution. Gamma protects search space diversity and prevents premature convergence to local optima. In our hybrid model, these parameters guide the search for ideal feature groups that improve the XGboost model's heart disease detection. By carefully modifying Alpha, Beta, and Gamma, we ensure a balanced exploration and exploitation of the search space, resulting in more accurate and reliable predictions.

3. Results and Analysis. The proposed model has been implemented with help of the Python language. The details of the Experimental Setup has been depicted in Table 2.

Table 2: Experimental Setup

Software	
XGBoost Library	Version 1.5.0
programming Language	Python
Python Libraries	Scikit-learn, Pandas, NumPy, etc.
Hardware	
CPU	Intel Core i7-10700K, 3.8GHz, 8 cores, 16 threads
RAM	32GB DDR4
GPU (Optional)	NVIDIA GeForce RTX 2080 Ti, 11GB VRAM
Storage	1TB SSD

Wolf Search Algorithm (WSA) hyperparameter tuning for XGBoost is a unique and successful cardiac issue detection method (Hudson et al., 2024; Jiang et al., 2024; Mondal et al., 2024; Zanfardino et al., 2024). WSA optimization uses wolf hunting behavior and is effective. WSA leverages wolf pack intelligence to efficiently explore XGBoost hyperparameter space. Table 3 depicts the default and optimized values for various hyper-parameters as below: Table 3: Default and optimized values

Parameter	Default Value	Optimized Value
Learning Rate	0.3	0.1
Maximum Depth	6	8
Number of Trees	100	150
Subsample Ratio	0.8	0.9
Column Subsampling	0.8	0.7

Lambda (L2 regularization)	1	0.5
Alpha (L1 regularization)	0	0.1
Gamma	0	0.2

Cardiovascular problem identification often involves analyzing complex, multi- dimensional data from genomic data, patient records, medical imaging, electrocardiograms (ECGs), and medical imaging. XGBoost is known for handling non-linearity, feature interactions, and missing data well. Improved model performance by WSA optimization of XGBoost's hyperparameters may improve heart disease diagnosis (Han- nan et al., 2024; Wang et al., 2024).

SHAP (SHapley Additive exPlanations) values help understand machine learning model predictions. They illuminate features' relative importance in model output for a specific situation (Kononova et al., 2024; Sood, V et al.,2023). SHAP values explain individual predictions to help understand how each characteristic affected the overall forecast for a data point. This information helps explain a model's forecast. SHAP values can illuminate predictions and model behavior. Figure 4 determine the features' global relevance and impact on the model's predictions by combining their SHAP values across the dataset (CASTAÑO et al., 2024).

Fig 4.1 demonstrates the SHAP Values of the Hyper-parameter.

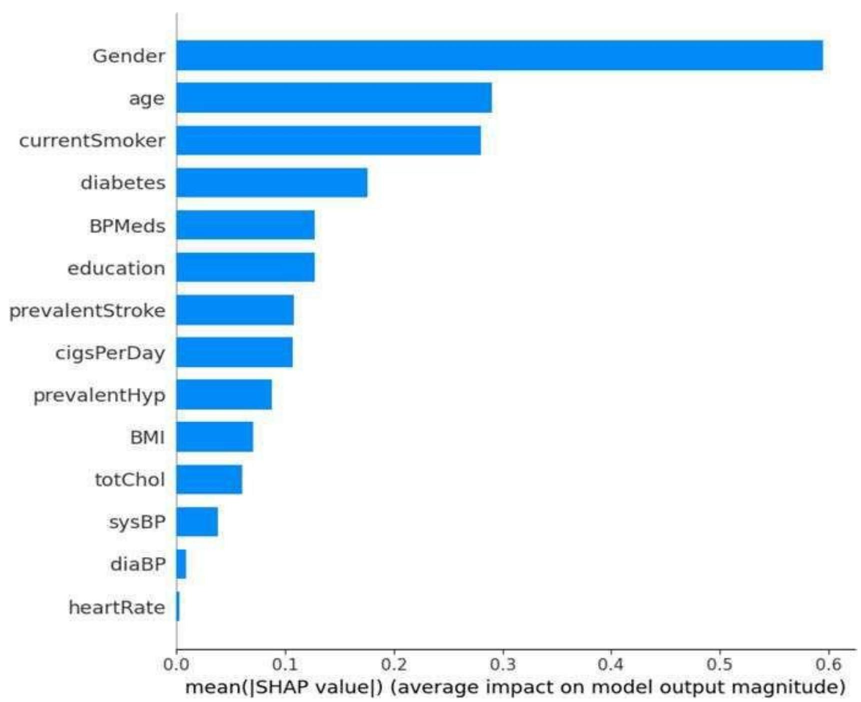

FIG. 4.1. *SHAP Values*

Wolf Search Algorithm and XGBoost for heart disease diagnosis are computer science and health informatics hybrids. This interdisciplinary alliance could offer groundbreaking ideas that improve medical diagnosis and treatment. Accurate heart disease identification allows personalized medicine projects to tailor treatments to each patient's risk variables (CASTAÑO et al., 2024; Nyström et al., 2024; Vahab et al., 2024; Zhu et al., 2024). Improving XGBoost with WSA could create models that better identify cardiac issues and reveal risk factors and therapies. Improved cardiac disease diagnosis has therapeutic implications for early detection, prognosis, and therapy planning. Researchers and doctors can improve patient outcomes, save healthcare costs, and reduce system pressure by constructing more accurate predictive models with WSA and XGBoost. Fig 4.2 demonstrates the history plot of the Hyper- parameter optimization.

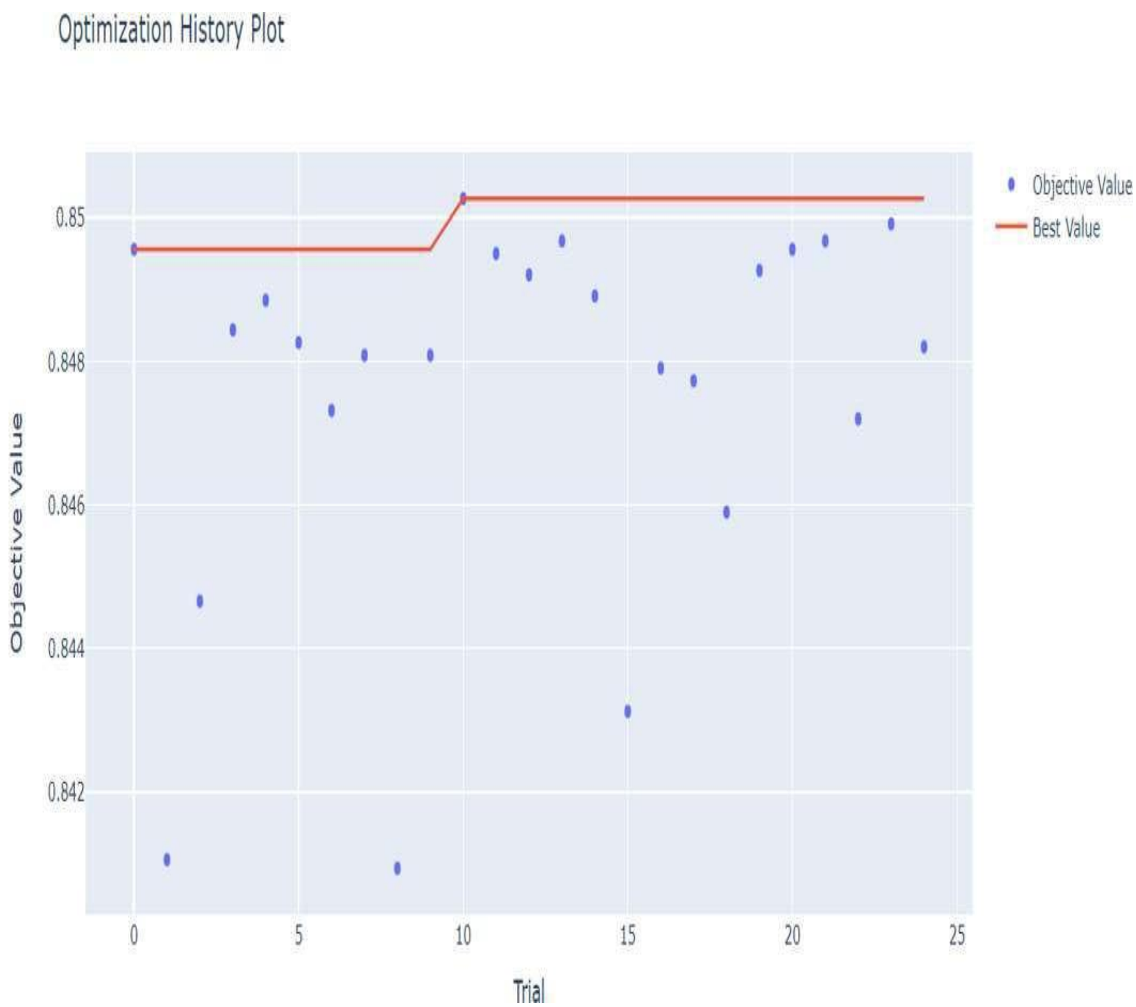

FIG. 4.2. *Hyper-parameter optimization History Plot*

Building and analyzing a confusion matrix helps researchers and practitioners assess the WSA-XGBoost model's heart disease detection accuracy and determine how to enhance and use it.

Fig 4.3 demonstrates the Confusion Matrix.

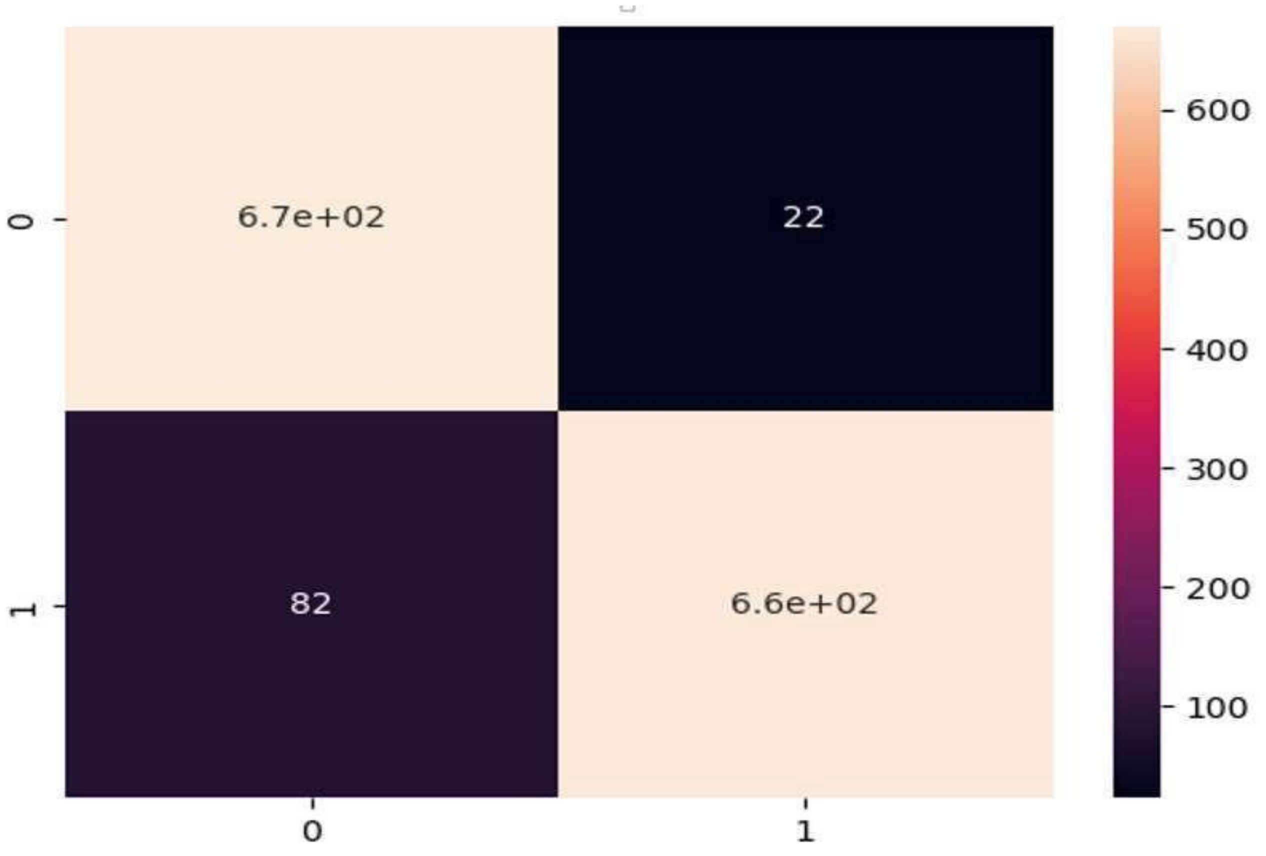

FIG. 4.3. *Confusion Matrix*

From the confusion matrix, the authors calculate various performance metrics to assess the model's accuracy, precision, recall, F1 score, and other relevant metrics. Table 4 depicts the performance of the proposed model as below.

Table 4: Performance of Proposed Model

Attribute	Precision	Recall	F1-score	Support
	0.97%	0.89%	0.93%	752
	0.89%	0.97%	0.93%	686
Accuracy			0.93%	1438
macro avg	0.93%	0.93%	0.93%	1438
weighted avg	0.93%	0.93%	0.93%	1438

Wolf Search Algorithm and XGBoost for heart disease diagnosis are computer science and health informatics hybrids. This interdisciplinary alliance could offer groundbreaking ideas that improve medical diagnosis and treatment. Accurate heart disease identification allows personalized medicine projects to tailor treatments toeach patient's risk variables. Table 5 shows the result comparison achieved by various traditional machine learning models with the proposed model as below.

Table 5: Result Comparison of Proposed Model

Methods	Accuracy	Precision	Recall	F1-score
Logistic regression	77.3%	76.1%	79.6%	77.8%
K Nearest Neighbors	81.4%	77.9%	84%	81.9%
SVM	79.1	76.3	84.7	80.3
Decision Tree	67.7%	65.5%	75%	69.9%
Random Forest	91.6%	76.2%	79.8%	76.9%
Adaboost	77%	75.9%	78.7%	77.9%
Gradient Boosting	77.3%	74.9%	81.6%	78.1%
XGBoost	76.9%	74.8%	80.7%	77.6%
CatBoost	77.3%	75%	81.4%	78.1%
Proposed Method	97.3%	97%	89%	93%

Class imbalance is common in medical datasets, especially heart disease datasets. Handling class imbalance properly is crucial for good predictions with machine learning models like XGBoost. There are several ways to reduce class imbalance and in- crease model performance utilising the Wolf Search Algorithm (WSA) and XGBoost. Data-level methods like oversampling the minority class or under sampling the majority class can be used. SMOTE (Synthetic Minority Over-sampling Technique) creates minority class synthetic samples for a balanced dataset. Algorithm-level approaches can also change class weights during training. XGBoost's scale weight option can be modified to balance classes by giving them F1-score, and AUC−ROC provide a more complete assessment of a model′s performance on imbalanced datasets than accuracy. WStune XGBoost model hyperparameters. The Weighted Support Vector Algorithm(WSA) helps enhance cardiac disease prediction. Improving XGBoost with WSA could create models that better identify cardiac issues and reveal risk factors and therapies. Improved cardiac disease diagnosis has therapeutic implications for early detection, prognosis, and therapy planning. Fig 4.4 demonstrates the result analysis.

	Logistic Regression	K Nearest Neighbors	Support Vector Machines	Decision Tree	Random Forest	AdaBoost	Gradient Boost	XGBoost	CatBoost	Proposed Model
Accuracy	0.773	0.814	0.791	0.677	0.916	0.77	0.773	0.769	0.773	0.973
precision	0.761	0.779	0.763	0.655	0.762	0.759	0.749	0.748	0.75	0.97
recall	0.796	0.84	0.847	0.75	0.798	0.787	0.816	0.807	0.814	0.89
f1-score	0.778	0.819	0.803	0.699	0.769	0.779	0.781	0.776	0.781	0.93

FIG. 4.4. *Result Analysis*

Combining the Wolf Search Algorithm (WSA) with the XGBoost model could speed up and improve heart disease detection. The Wolf Search Algorithm optimises complex search areas based on how wolves hunt together. Hyperparameters can be optimized better by integrating WSA with XGBoost, a robust gradient boosting framework. This hybrid technique combines WSA's exploratory strength to determine the best parameter values to improve the model's cardiac detection. WSA's global search and XGBoost's prediction power may improve cardiology patient care and treatment regimens by providing more accurate and reliable diagnostic results.

Researchers and doctors can improve patient outcomes, save healthcare costs, and reduce system pressure by constructing more accurate predictive models with WSA and XGBoost.

Our work shows that the Hybrid Wolf Search Algorithm (HWSA) and XGBoost model may reliably diagnose cardiac issues, but real-world implementations must consider certain limits and risks. Starting with reliable and representative training data is essential for any ML model, including the HWSA-XGBoost hybrid. Incompleteness, noise, and biases might affect clinical model performance and diagnostic outcomes. Second, hybrid models that combine complex machine learning methods like XGBoost with heuristic algorithms like Wolf Search Algorithm may make clinical decision-making harder to explain. To foster trust and acceptance in healthcare, models must be interpretable and transparent so doctors may understand prediction. When considering how to integrate our model into clinical operations, computing requirements and scalability must be considered. Healthcare real-time applications require algorithms that can manage enormous datasets and provide accurate projections quickly. Additionally, we must determine if our findings apply to diverse patients and healthcare settings. Demographics, disease prevalence, and treatment regimens may alter the HWSA-XGBoost model's efficacy in various clinical settings. Finally, ethical issues including patient privacy, data security, and healthcare dis-

parities should be considered before using any AI-driven diagnostic tool in clinical practice. Even though our work shows promising heart illness diagnosis results using the HWSA-XGBoost hybrid model, these restrictions and risks must be addressed for responsible and successful clinical integration. Future research should improve AI-powered medical solutions' trustworthiness, understandability, and morality.

Due to cardiac data complexity and variability, previous investigations used simple algorithms or outmoded statistical methodologies. We studied hybrid models with XGBoost and Wolf Search to overcome this constraint and improve precision and resilience. Due to their incapacity to deliver clear results or control feature selection, several modern models fail to identify heart disease causes. We overcome this gap with a hybrid model architecture and feature selection technique. Large datasets or real-time clinical settings may challenge existing models' scalability. To overcome practical constraints, our method optimizes computing efficiency and forecasting accuracy. Lack of validation across demographic and clinical populations limits the generalizability of prior studies' conclusions. We tested the hybrid model in various patient demographics and clinical settings to confirm its efficacy.

4. Conclusion and Future scope. Metaheuristic optimization methods like WSA mimic wolf hunting. XGBoost hyperparameter tuning may consistently detect cardiac disorders in classification tasks. WSA can quickly explore XGBoost's hyperparameter space to find the optimum cardiac disease categorization settings. WSA may alter learning rate, tree depth, regularization parameters, and tree count to optimize XGBoost performance. XGBoost scores features' relevance in predicting the target variable. Assessment of features can provide the most relevant clinical characteristics or biomarkers for heart illness diagnosis. This study can help analyze model predictions and choose features. After hyperparameter modification and model training, the XGBoost classifier's accuracy must be evaluated. These tests assess the model's heart condition classification accuracy while eliminating false positives and negatives. The trained model must be durable through cross-validation. These factors can estimate model generalization on unknown data. This is crucial for assessing the model's performance on different data subsets and avoiding overfitting. Decision trees and feature significance plots help interpret XGBoost models. Cardiology researchers and doctors can benefit from understanding the model's decision-making process. Interpretability is especially important for healthcare applications where domain experts must understand machine learning models' decision-making processes. Using WSA for hyperparameter tuning and XGBoost for classification, cardiac illnesses can be accurately identified. The enhanced XGBoost model distinguishes cardiac disorders utilizing clinical data and biomarkers well. This strategy may help doctors diagnose cardiac disease early, assess risk, and plan treatment. WSA and XGBoost provide a solid framework for creating interpretable heart disease detection models to improve patient outcomes and clinical decision-making in cardiology.

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