RESEARCH ARTICLE

Ischemic Heart Disease Prediction Using Optimized Squirrel Search Feature Selection Algorithm

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ABSTRACT In recent years, the volume in globally recognized medical data sets are increasing both with attributes and number of records. Machine learning algorithms aiming to detect and diagnose ischemic heart diseases requires high efficacy and judgment. The state of art Ischemic heart disease data sets presents several issues, including feature selection, sample size, sample imbalance, and lack of magnitude for some characteristics etc. The proposed study is primarily concerned with improving feature selection and reducing the number of features yet giving better decisions. In this study, to pick salient aspects of heart illness, an improved squirrel search optimization algorithm with a meta-heuristic approach is proposed. Comparison study of the proposed ischemic heart disease squirrel search optimization (IHDSSO) model in conjunction with random forest classifier ensures better feature selection and accuracy over 98% with respect to other state-of-the-art optimization algorithms.

INDEX TERMS Machine learning, feature selection, squirrel search algorithm, random forest algorithm, University of California Irvin dataset.

I. INTRODUCTION

Today's generation is exceedingly full of activity in their daily routine agenda, which causes anxiousness, and stress. The heart rate and blood pressure of each individual are different, Pulse rates range from 60 to 100 beats per minute, while blood pressure ranges from 120/80 to 140/90. Worldwide, Heart Disease(HD) is the leading cause of death. "Cardio" means "heart." Cardiologist disease is a category of heart disease. The various types of cardiac disease are Coronary artery disease, Myocardial infarction, Hypertrophic cardiomyopathy, Arrhythmia, Dilated cardiomyopathy, Heart failure, Mitral regurgitation, and Congenital heart disease.Nowadays, heart disease is the leading cause of death worldwide. Predicting heart disease is a complex task since it requires experience along with advanced knowledge [1], [2]. Various methods, such as the K-Nearest Neighbor Algorithm (KNN), Naive Bayes(NB), Decision Trees (DT), and Genetic Algorithm (GA), are used to categorize the severity of the

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HD problem. Because the nature of the HD is complex, it must be treated with carefulness. Failure to do so could injure the heart or lead to death. Medical research and machine learning (ML) are being utilized to find various kinds of metabolic disorders. In the classification of HD and data analysis, ML with categorization plays a significant character [3].

"Data mining also referred to as knowledge discovery from data (KDD), is the automated extraction of patterns considering knowledge captured in large databases, the web, warehouses, other huge information repositories or data streams" [4]. According to a world health organization (WHO) report [5], 17.9 million people died from cardiovascular disease (CVD) in 2016, accounting for 31% of all deaths globally. Stroke or heart attack accounts for 85 percent of these deaths. CVD fatalities account for three-quarters of all deaths, primarily in developing countries, low- and middle-income countries are affected. Of the 17 million deaths that occur too soon caused by non-communicable diseases in 2015, 82% were in countries with a low and moderate-income, and CVDs affected 37%. There is a need

to detect CVDs, and data mining algorithms can be used to achieve this [6], [7] A factor in data analytics that degrades productivity is missing data. An incorrect imputation may lead to incorrect prediction of missing values [8].

The best optimization algorithms in the world, known as meta-heuristics, have several benefits, including robustness, performance reliability, simplicity, ease of implementation, etc [9]. The goal of feature selection is to minimize the number of dimensions in our data, which may increase its generalization [10]. Because of the large amount of data, feature selection has become more important. Hybrid methods are more widely utilized in Feature Selection(FS) due to the computing difficulty of wrapper methods, filtering techniques' low performance, and embedding approaches' reliance on classifiers. Filtering metrics are used in hybrid techniques to minimize the computational complexity of wrapper algorithms, and they have been shown to provide better feature subsets. Although filtering metrics select features based on their importance, the majority of them are insecure and subjective toward the metric in question. Furthermore, the selection of filtering metrics is heavily influenced by the data distribution and data kinds [11] squirrel search algorithm (SSA) is an FS algorithm, a nature-inspired metaheuristic method, which was introduced in the year 2019. The goal of SSA is to emulate southern flying squirrels' dynamic foraging and gliding behavior. These behaviors are mathematically represented to emphasize exploitation and exploration in a specific search space [12]. An improved squirrel search algorithm (ISSA) was introduced to increase the efficiency and robustness of SSA. The progressive search approach and the leaping search method, both of which have an independent winter search strategy during the early evolutionary period, are included in the ISSA algorithm. The results of the experiments suggest that the ISSA algorithm can increase convergence accuracy, speed up convergence, and maintain population variety. In comparison to SSA, the statistical test shows that ISSA has substantial advantages [13]. The dataset information is obtained from Cleveland UCI heart disease and contains 303 instances with 76 attributes, out of only 13 of them are taken into account. Because they contain significant healthcare records, all of the features are important. The selection was based on the recommendation of a cardiac department expert. Clinical data are essential for determining the severity of cardiac disease and diagnosing it.

Recently, optimization has become even more crucial to our daily lives. Popular and widely utilized in many engineering domains are population- and evolutionary-based optimization techniques. This optimization approach intelligently selects the finest of the many possibilities accessible and offers a conducive setting for problem-solving. The majority of optimization techniques demand a mathematical model of the system [14]. It might be challenging to create a mathematical model for complicated systems. Even if the model is established, the high cost prevents using the solution time. To acquire adequate global and local search operators,

it is difficult to build an optimization algorithm because of physical events [15].

II. RELATED WORKS

Jijesh et al. [16] created a supervised learning-based decision support system for multisensory healthcare data from wireless body sensor networks. The SSA is used to select features. Other methodologies such as Conventional Neural network, Deep Belief Network, and Artificial Neural Network are compared to the proposed M-DBN (modified deep belief network) technique. The proposed method outperforms all other techniques currently in use. Based on data mining techniques, Shan et al. [17] suggested a more accurate and practical risk prediction system. To reduce dimensionality, CFS Subset Evaluation was used with the Best-First-Search approach to picking key characteristics. The data is taken from the Cleveland Heart Disease Database and PKU People's Hospital's Cardiology inpatient dataset. SVM takes twice as long as the random forest classifier.

To pick salient aspects of heart disease, an imperialist competitive algorithm with a meta-heuristic approach is proposed in this paper [18]. In comparison to other optimization algorithms, this approach can deliver an additional best solution for FS toward genetics. The categorization is also done using the K-nearest neighbor approach. The efficiency of the FS method improved by applying the proposed algorithm, according to the evaluation results. The data for these tests came from the UCI ML repository's HD data and the Tehran Shahid Rajaei hospital. The method proposed by Fuad et al. [19] is feature optimization, which aims to find the better variable size n-gram attributes for the supervised ML, also known as "discrete weights based n-gram feature selection." Preprocessing, appropriate attribute selection, attribute FS, and the classification approach used to predict the extent of the disease in a specific patient's medical records are all things to think about.

An Internet of Medical Things framework for the analysis of HD based on modified salp swarm optimization (MSSO) and an adaptive neuro-fuzzy inference system (ANFIS) is presented to increase prediction accuracy. The Levy flight method, the proposed MSSO-ANFIS improves search abilities. For all iterations, the suggested Levy-based crow search algorithm for FS acquired the maximum fitness values. When compared to existing approaches, the suggested MSSO-ANFIS strategy provides superior F1-score, precision, accuracy, and recall as well as the lowermost classification error [20].

Mohit et al. [12] introduce the SSA, a revolutionary nature-inspired optimization paradigm. Glid-ing is a powerful mechanism that small mammals employ to traverse large distances. In terms of convergence rate and optimization accuracy, thorough comparative research is conducted to demonstrate the efficiency of SSA over other familiar optimizers. To test its applicability and resilience, the suggested technique is applied in real-time HD research. In comparison to other

existing optimizers, the final results show that SSA gives better accurate solutions with a higher convergence rate.

For biomedical datasets, a robust filtering approach based on rank aggregation was developed in a hybrid FS model using the ISSA. Experiments on 9 biomedical data sets and three distinct classifiers demonstrate the resilience of our proposed model. The suggested technique beats previous models in terms of classification accuracy and computing time, according to the experiments. It has also been demonstrated that it reduces dimensionality to a greater extent [16]. Yanjiao et al. [13] proposed an ISSA. The suggested algorithm includes two searching methods: one is a jumping search, and the other is a progressive search. The SSA practical technique is selected automatically using a linear regression selection strategy, which improves the algorithm's robustness. The 'escape' operation in the jumping search method sufficiently develops the search space, while the 'death' operation further explores the developed space, balancing SSA's development and exploration abilities. The results of the experiments suggest that the proposed algorithm can increase convergence accuracy, speed up convergence, and maintain population variety.

An enhanced form of SSA called ISSA is suggested to improve global convergence capabilities. To begin, an adaptive predator presence probability technique suggested the algorithm's exploitation and exploration capabilities. Second, the randomness and fuzziness of flying squirrel foraging behavior are explained using a normal cloud model. The selection method between succeeding spots is implemented to uphold the greatest position of flying squirrel individuals. Finally, a dimensional search enhancement method is used to advance the algorithm's local search capability. When compared to advanced optimization methods like SSA, PSO, FOA, IFFO, and CMFOA, experimental test results show that ISSA performs well [21].

Kader et al. [22] have compared five metaheuristic algorithms used in the Covid19 team formation problem. Based on the ideal findings the crow search algorithm was the effective metaheuristic method. The modified Huber independent component analysis-based SSA [23] effectively reduce data dimensionality by combining modified Huber independent component analysis and the SSA. In an Infrastructure as a Service cloud environment, Sanaj et al. [24] propose a chaotic SSA(CSSA) for efficient multitask scheduling. The early ecosystem was developed with chaotic optimization for the efficient ecosystem to permit more global convergence. To enable the exploring authority to complement SSA methods, the suggested CSSA was finally produced the messy limited search.

Mesfer et al. [25] introduce a unique "multi-objective squirrel search optimization algorithm with a stacked autoencoder" (MOSSA-SAE)model for Financial Crisis Prediction in an IoT background. The MOSSA-SAE technique includes several sub-processes, including pretreatment, processing, and analysis. Handling class imbalances, parameter tuning, and categorization The MOSSA-SAE approach, for example,

allows IoT devices such as smartphones to communicate with each other. Users' financial information is collected through computers, tablets, and other devices. For additional analysis, the data is sent to the cloud. Ponnuvel et al. [26] have proposed a study to handle the single area multi-fuel economic dispatch (SAMFED) and MAMFED problems, a Fuzzified SSA (FSSA) is proposed in this study. For unconstrained and limited portfolio optimization issues, Mahdi et al. [27] designed and adapted an SSA. For portfolio optimization, the suggested SSA metaheuristic technique is compared to a range of approaches reported in the works, including conventional single metaheuristics, hybrid meta-heuristics, and multi-objective optimization approaches. The comparative analysis and computational findings utilizing various performance evaluations reveal that the suggested method is superior to both extended Mean-Variance and Sharpe models for unconstrained portfolio optimization. The suggested method has also produced very competitive results for the diverse methods used in the limited form of the issue. The RFE (recursive feature elimination) technique is used to select features. [28] [18]. Senthilkumar et al.[1] provide a unique ML-based model for selecting relevant features, which increases the accuracy of cardiovascular disease(CVD) classification. The prediction model is shown using a variety of feature combinations and many well-known classification strategies. Through the HD classification model using a hybrid RF and a linear model. Achieve a higher level of performance with an accuracy rate of 88:7%.

The Relief and Least Absolute Shrinkage and Selection Operator approaches are used to find suitable features [29]. To allow for comparisons, the findings are presented individually. The most accurate results were obtained by applying the relief and LASSO model. Jasmine et al. [30] did a study on evolutionary computing-based feature selection strategies, their advantages and disadvantages, and their contribution to CVD classification. According to the understanding study, having a larger number of features can lead to misclassification and overfitting. Anuradha et al. [31] offered a Feature Importance ranking of 2 gradient boosting algorithms, XGBoost and CatBoost.Subsets of features were generated using the relevance rating of each character as a threshold. On these subsets, the classifiers Majority voting ensemble, XGBoost, and CatBoost were used to model them, and the feature subset with the maximum accuracy was found. When calculating the value of a subset of attributes, the correlation-based FS method analyses the individual classify capacity of each attribute as well as the degree of redundancy between them [32].

III. MATERIALS AND METHODS
A. DATA SET
The dataset is a collection of connected data, with a report for each instance based on the data it represents, and an attribute for each attribute in the dataset. This study uses data from "Cleveland, Switzerland, Long Beach, and Hungary",

TABLE 1. Heart disease attributes.

Attribute	Description	Domain of value
Age	Age in years	29 to 77
Sex	Sex	Male(1) Female(0)
Cp	Chest pain type	Typical angina (1) Atypical angina (2) Non-anginal (3) Asymptomatic (4)
Trestbps	Resting blood sugar	94 to 200 mm Hg
Chol	Serum cholesterol	126 to 564 mg/dl
Fbs	Fasting blood sugar	>120 mg/dl True (1) False (0)
Restecg	Resting ECG result	Normal (0) ST-T wave abnormality (1) LV hypertrophy (2)
Thalach	Maximum heart rate achieved	71 to 202
Exang	Exercise induced angina	Yes (1) No (0)
Oldpeak	ST depression induced by exercise relative to rest	0 to 6.2
Slope	Slope of peak exercise ST segment	Upsloping (1) Flat (2) Downsloping (3)
Ca	Number of major vessels coloured by fluoroscopy	0–3
Thal	Defect type	Normal (3) Fixed defect (6) Reversible defect (7)
Num	Heart disease	0–4

as well as data from the UCI repository [33] and Kaggle [34] for data investigation. There are 76 features in the data set, 14 of which are quite beneficial in identifying heart disease. In most cases, the predictive class attribute comes last. The attributes' data set specifications are shown in Table 1.

B. SIGNIFICANCE OF THE ATTRIBUTE
Every single property in the UCI HD dataset is thought to be important for HD prediction, and the importance of each one has been labeled as a hyperparameter. Table 2 shows the importance of the property, description, domain value, and hyperparameter.

IV. OVERVIEW OF FEATURE SELECTION TECHNIQUES
The process of reducing the number of input variables in a model is called feature selection. The total number of input variables is minimized to reduce the cost of modeling and, and to increase the model's performance. Statistical-based FS methods are used to statistics the relationship between the input variable and the target variable, then selecting the input variables with the strongest relationship. Although the statistical measures utilized are influenced by the type of data in both the input and output variables, these processes can be swift and successful. As a result, when performing filter-based analysis, an ML practitioner may find it difficult to select an appropriate statistical measure for a dataset. Figure 1 depicts an overview of FS approaches.
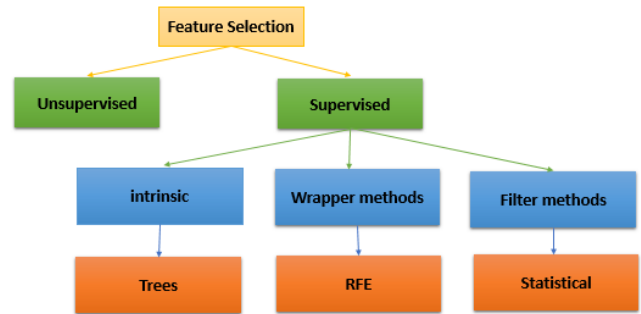

FIGURE 1. Overview of feature selection techniques.

In supervised techniques, the wrapper, filter, and intrinsic methods are used. Filter-based FS approaches score the correlation or dependence between input variables using statistical measures, which can then be filtered to find the most important features. The data type of the input variable and the output or response variable must be carefully considered while developing statistical measures for FS.
- Unsupervised: The target variable should not be used. Example: Correlation
- Supervised: Use the target variable.
- Wrapper: Look for feature subsets that perform well. Example: Recursive Feature Elimination
- Filter: Subsets of features should be chosen depending on their relation to the aim. Example: Statistical Methods
- Intrinsic: Algorithms that select features automatically during training. Example: DT

The following list of factors explains the necessity of metaheuristic algorithms [35]:
1) An optimization problem's structure could be such that it is impossible to define how to discover the precise answer.
2) From the perspective of the decision maker, the comprehensibility of metaheuristic algorithms can be much simpler.
3) Metaheuristic algorithms can be utilized for learning as well as the process of determining the precise solution.
4) Typically, definitions created using mathematical formulas overlook the trickiest aspects of real-world problems. Using flawed data to determine model parameters might result in far higher errors than using a metaheuristic technique, which only provides a partial solution.

A. SQUIRREL SEARCH ALGORITHM
The SSA is a dynamic foraging movement of southern FLS in deciduous forests of Asia and Europe by gliding, a successful strategy utilized by tiny mammals for long-distance travel [21]. During the summer, the squirrels move their places by gliding from one forest tree to the next, looking for foodstuff. They can simply locate acorn nuts to meet their daily energy requirements. Then they start looking for hickory nuts that have been kept for the winter. During the winter, they become less active and rely on the storage of

TABLE 2. Significance of the attribute.

Attribute	Description	Domain of value	Significance of the attribute in 2 or 3 points so as to designate it as one of the hyper parameter
Age	Age in year	29 to 77	Higher the age, higher the risk of developing coronary artery disease. This happens irrespective of gender, although women tend to be about a decade older when they develop cardiovascular disease compared to men.
Sex	Sex	Male(1) Female(0)	Male sex is an independent risk factor for developing ischemic heart disease. However, women tend to have poorer outcomes following acute coronary syndromes. Women also have atypical symptoms and delayed presentations compared to men.
Cp	Chest pain type	Typical angina (1) Atypical angina (2) Non-anginal (3) Asymptomatic (4)	Presence of typical angina makes the diagnosis of ischemic heart disease much more likely compared to atypical angina. Non-anginal pain makes it less likely. Although uncommon, ischemic heart disease can present as silent ischemia (no symptoms related to ischemia) in elderly patients, diabetics especially with neuropathy etc. However, complete lack of symptoms in a younger, non-diabetic patient usually goes against significant coronary artery disease.
Trestbps	Resting blood sugar	94 to 200 mm Hg	Elevated blood sugar levels esp fasting blood sugar levels indicates either poor control of sugars in a known diabetic or the presence of diabetes in previous non-diabetic patients. Those with diabetes and ischemic heart disease do poorly if their blood sugars are not well controlled with medications.
Chol	Serum cholesterol	126 to 564 mg/dl	Elevated serum cholesterol levels esp. low density lipoproteins (LDL) is an independent risk factor for ischemic heart disease. Control of LDL levels to predefined targets based on the patient's risk profile is one of the main goals of therapy for ischemic heart disease.
Fbs	Fasting blood sugar	>120 mg/dl True (1) False (0)	Elevated blood sugar levels esp fasting blood sugar levels indicates either poor control of sugars in a known diabetic or the presence of diabetes in previous non-diabetic patients. Those with diabetes and ischemic heart disease do poorly if their blood sugars are not well controlled with medications.
Restecg		Male(1) Female(0)	Normal resting ECG does not rule out the presence of ischemic heart disease. Stress testing like treadmill exercise testing may be required. Presence of LVH can interfere with the diagnosis of ischemia from both the resting ECG and during treadmill exercise testing.
Thalach	Maximum heart rate	71 to 202	Maximum heart rate achieved during treadmill exercise testing indicates completeness of the test (in general, we need the person undergoing TMT to achieve a heart rate of more than 85% of maximum age predicted heart rate). If the patient achieves a heart rate lesser than this, TMT is regarded as inconclusive. If the target heart rate is achieved, then we can go on to interpret the TMT further and based on the presence, type and degree of ST-T changes, probability of underlying ischemic heart disease is estimated.
Exang	Exercise induced angina	Yes (1) No (0)	Exercise induced angina is an important indicator of significant coronary artery disease. However, it can also be seen in aortic stenosis.
Oldpeak	ST depression induced by exercise relative to rest	0 to 6.2	Larger the ST depression esp. if seen in multiple contiguous ECG leads, higher the likelihood of underlying ischemic heart disease.
Slope	Slope of peak exercise ST segment	Upsloping (1) Flat (2) Downsloping (3)	Order of importance from most to least important: Down sloping, flat followed by upsloping. Upsloping ST depression is the least important.
Ca	Number of major vessels coloured by fluoroscopy	0–3	Coronary angiogram is a diagnostic test used to confirm the presence of coronary artery disease. More the number of vessels affected, worse the clinical outcome for the patient.
Thal	Defect type	Normal (3) Fixed defect (6) Reversible defect (7)	A reversible defect is specific for significant obstruction in one or more coronary arteries. A fixed defect may be seen in those who have infarcted areas indicating previous MI. Normal perfusion study indicates a low chances for having coronary artery disease.

hickory nuts to meet their energy needs. Flying squirrels become busier as the temperature warms. The SSA is built on the foundation of the above-mentioned process, which is repeated and continues throughout the squirrels' life span. It is a population-based technique in which each squirrel forages for food by moving around a multi-dimensional search space. The distance of the food from the squirrel individual is equivalent to the fitness value of the objective function, and the placements of squirrels are considered various design variables. Individual squirrels in SSA change

their places and move to better ones. It assumes that there are n squirrels in a deciduous forest and that each tree has only one squirrel. The three types of trees are considered to be present in the forest. Normal, Acorn, and Hickory are the three types of trees. The forest is meant to feature N trees, one of which is a hickory tree, no acorn trees, and the rest are ordinary trees with no food. For squirrels, the hickory tree is the finest foraging location. The SSA is a foraging behavior simulation of a squirrel. Each squirrel uses four mechanisms to shift its position: population distribution, dynamic feeding behavior, seasonal adaptive intelligence, and random relocation of individuals at the end of the winter.

Squirrel Search Algorithm incorporates a seasonal monitoring condition which facilitates the advantages of better and more efficient search space exploration. In addition, SSA aids to obtain the overall outcomes that balance exploration and exploitation challenges and eradicate over-fitting issues. However, SSA shares certain drawbacks with other intelligent evolutionary algorithms, such as poor convergence accuracy and slow convergence speed.

1) KEY STEPS IN SSA
Based on the nutrition foraging behavior of FLS, the optimization of SSA can be theoretically characterized by the following steps.

Step 1 (Initialize the Parameters): "The total number of iterations Im, population size NP, the total number of decision variables Nd, predator presence probability Ppp, scaling factor Fs, gliding constant Cg, and upper and lower bounds for decision variables Ud and Ld. These options are selected at the start of the SSA process".

Step 2: Random Initialization of Flying Squirrels SSA, like other population-based algorithms, begins with a random location of flying squirrels. In a forest, there are a specific number of flying squirrels (FLS), and their location can be set. The initial position of each FLS in the forest is determined using a uniform distribution. The positions of the FLS are randomly initialized in the search algorithm as follows:

$$FLS_{i,j} = Ld + rand() * (Ud - Ld)$$
$$i = 1, 2, \ldots, Np, \; j = 1, 2, \ldots, Nd \quad (1)$$

where rand() returns a random number with a uniform distribution in the range [0, 1].

Step 3 (Fitness Evaluation): The fitness of each FLS is determined by entering the values of the decision variable into a user-defined fitness function and computing the corresponding values. The fitness value of each FLS's position indicates the type of food supply it is looking for, such as optimal, normal, or no food source, and hence its chances of survival. By entering the values of choice variables into a fitness function, The location of an individual flying squirrel's fitness value f = (f1f2,..., fNP) is computed as follows:

$$f_i = f_i(FLS_{i,1}, FLS_{i,2}, \ldots . FLS_{i,n}) \quad (2)$$

$i = 1, 2, \ldots NP$

Step 4: Sorting, Declaration, and Random Selection

After recording the fitness values of each FLS position, the array is sorted in ascending order. A FLS with a poor fitness value lives in the hickory nut tree. The next 3 finest FLS are thought to be on acorn nut trees and will eventually migrate to hickory nut trees. The FLS that are left should be on normal trees. Some squirrels are thought to be moving to the hickory nut tree based on random selection, presuming they've met their daily calorie needs. The surviving squirrels will make their way to the acorn nut trees. The presence of predators always affects the FLS' foraging behavior. Sort the index concerning ascending order. The fitness value of the FLS' locations is then used to rate the quality of food sources in ascending order:

$$[sorted\_f, sort\_index] = sort(f) \quad (3)$$

Step 5: Generate new locations through Aerodynamic Gliding

In each instance, it is supposed that in the lack of a predator, The FLS glides and searches the forest effectively for its preferred meal, but in the presence of a predator, it is forced to do a little random walk to find a nearby hiding site. Creating a new location by gliding is:

$$FLS_{at}^{new} = \begin{cases} FLS_{at}^{old} \\ +dgCg(FLS_{ht}^{old} - FLS_{at}^{old}), & \text{if R1} \geq \text{Ppp} \\ \text{random location}, & \text{otherwise} \end{cases} \quad (4)$$

where dg is random gliding distance and R1 is a function that returns a value from the uniform distribution on the interval [0, 1], Cg is a gliding constant, and R1 is a function that returns a value from the uniform distribution on the interval [0, 1]. The new position is estimated using aerodynamic gliding, either with velocity or random values. Move the new places while limiting their lower and higher bounds.

Step 6: Stopping Criterion The function tolerance criterion is a popular convergence criterion that specifies a small but permitted difference between the last two outputs. The maximum implementation time is occasionally used as a pausing condition. In this experiment, most iterations are used as a stopping condition.

V. METHODOLOGY
The first step of the Experiment workflow with the UCI HD data set has been loaded, and it is now ready for pre-processing. The 13 attributes "Age, Sex, Cp, Trestbps, Chol, Fbs, Restecg, Thalach, Exang, Oldpeak, Slope, Ca, and Thal" are selected from the preprocessed data set of HD. The RF algorithm was used to improve the classification accuracy. The confusion matrix is used to assess the model's performance. The experiment workflow is shown in Figure 2. This phase aims to select significant attributes, which will be useful in the classification of Ischemic Heart Diseases. The importance of the 13 attributes of the UCI HD datasets can't be overstated because they contain essential clinical details. These medical records are essential for determining the severity of HD and diagnosing it.

Algorithm 1 Algorithm for Ischemic Heart Diseases Squirrel Search Optimization

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Input: Initialize the population positions with random values with respect to lower bound and upper bound limit.

Output: converged solution.

1: Generate random location for n number of flying squirrels.

$$FLS_{i,j} = Ld + rand() * (Ud - Ld)$$

i = 1,2,…,Np, j = 1,2,…,Nd

2: Estimate the fitness value for the input features data for N number of samples based on the k neighbors and error rate.

$$f_i = f_i(FLS_{i,1}, FLS_{i,2}, ….FLS_{i,n})$$

i = 1,2,…NP

3: Sort the locations of flying squirrels in ascending order depending upon their fitness value.

$$[sorted\_f, sort\_index] = sort(f)$$

4: Generate new locations through Gliding

$$FLS_{at}^{new} = \begin{cases} FLS_{at}^{old} \\ +dgCg(FLS_{ht}^{old} - FLS_{at}^{old}), & \text{if } R1 \geq Ppp \\ \text{random location}, & \text{otherwise} \end{cases}$$

5: Repeat the steps 1 to 4 for maximum number of iteration.

TABLE 3. Confusion matrix.

Predicted Class / Actual Class	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Figure 3 shows the comparison of the existing Feature selection technique with the proposed ISSA method. The obtained significant attributes are given to an existing random forest classification algorithm to classify Ischemic Heart Diseases. The output of the confusion matrix is validated in terms of accuracy, Sensitivity, and Specificity, which will provide a more accurate classification result for the classification of Ischemic Heart Diseases.

Table details a typical confusion matrix. The mathematical background of various parameters associated with the confusion matrix are:

Accuracy: the proportion of instances that are correctly classified.

$$Accuracy = TP/(TP + FP + TN + FN)$$

Sensitivity: proportion of positive instances that are correctly classified as positive.
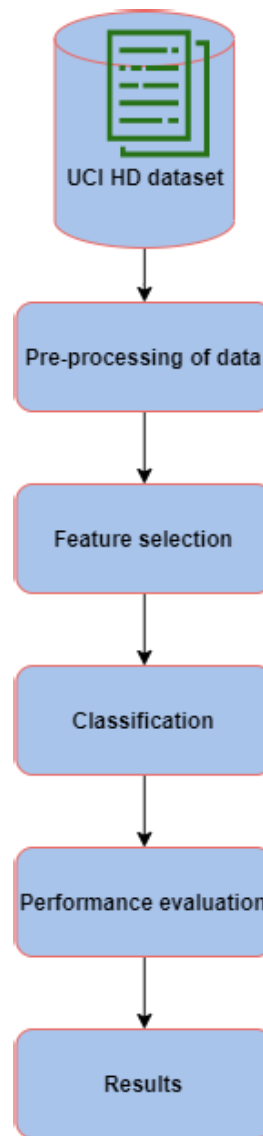
$$Sensitivity = TP/(TP + FN)$$

FIGURE 2. Experiment workflow with UCI HD dataset.

Specificity: proportion of negative instances that are correctly classified as negative.

$$Specificity = TN/(TN + FP)$$

f Score: An F-score is the harmonic mean of a system's precision and recall values.

$$f\ Score = 2 * (Recall * Precision)/(Recall + Precision)$$

where,

Precision: The number of true positives divided by the number of false positives plus true positives. Recall: the number of true positives divided by the number of true positives plus false negatives.

Kappa: Kappa is another single-value metric designed to help the algorithm assess performance among an array of classifiers. Kappa is designed to compare the performance of
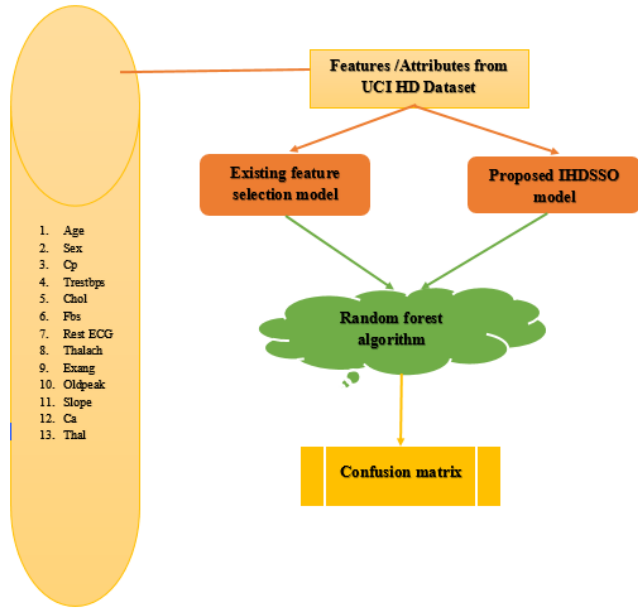
FIGURE 3. Performance comparison of the proposed IHDSSO model with existing mode.

any classifier to the baseline of a ''random classifier.''

Kappa = (total accuracy

−random accuracy)/(1 − random accuracy)

Figure 4 shows the overall system model for Ischemic Heart Disease Squirrel Search Optimization (IHDSSO). The input of the proposed model is taken from the benchmark UCI HD dataset with missing values. Firstly, the missing values in the data sets are recognized and imputed by using the Ischemic Heart Disease Multiple Imputation Technique. Algorithm 2 illustrates a fuzzy-based multiple imputation algorithm for missing data [36].To identify the important features, the imputed data is provided to the Improved Squirrel Search optimization as an input. To classify Ischemic Heart Diseases, the collected relevant features are fed into an existing random forest machine learning classification algorithm. The performance is analyzed by using a confusion matrix.

A. RANDOM FOREST(RF) ALGORITHM
In this work, a variety of ML methods are compared with the proposed IHDSSO. For the proposed IHDSSO model evaluation, the random forest classification technique is used. To improve prediction capability, RF employs the notion of bagging to aggregate many DT. Individual learners are trained independently in bagging. It uses replacement to generate several samples of data at random from the unique dataset, and each DT is trained on distinct models of data. During tree creation, features are also chosen at random. A majority vote is used to integrate predictions provided by various trees. Figure 5 depicts the Random Forest's operation. By optimizing parameters like as the total number of estimators, size of the smallest node, and amount of
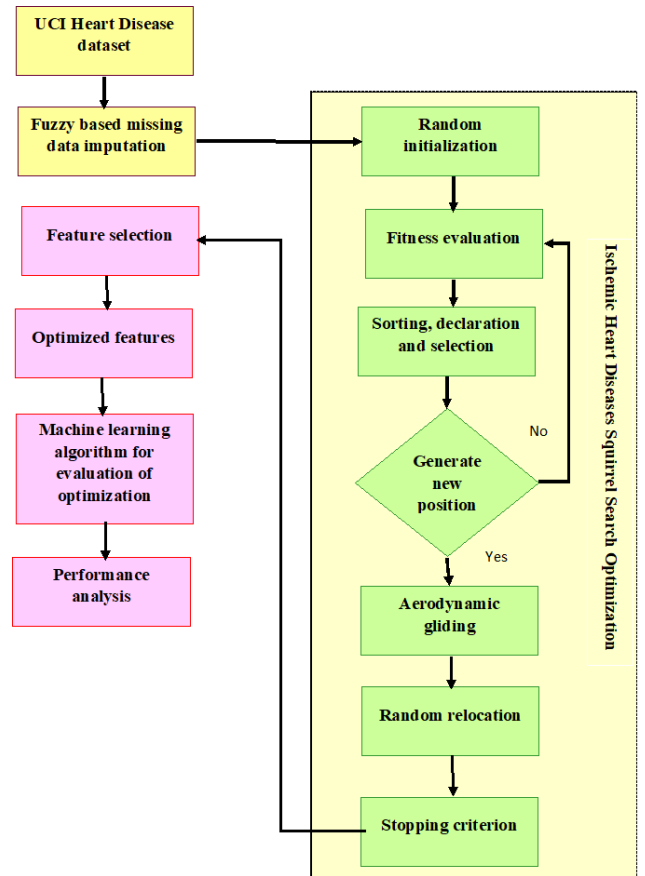

FIGURE 4. Ischemic Heart Diseases Squirrel Search Optimization(IHDSSO) overall System model.
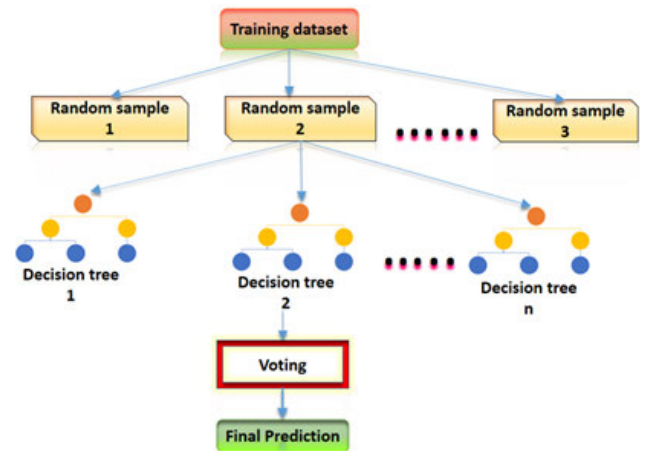

FIGURE 5. Random forest algorithm.

characteristics utilized to separate nodes, the RF can be modified for higher accuracy.

VI. RESULTS AND DISCUSSION
We have used the spider (python 3.8) compiler for the experimentation, the associated parameters are shown in table 4. Set the population's position at random values concerning the lower and upper bounds. The figure 6 shows the lower

Algorithm 2 Ischemic Heart Disease Multiple Imputation Technique [36]

Input: X, dataset with missing attributes.

Output: The dataset with imputed values.

    Begin

2: **foreach** y ∈ X **and** ContainsMissing(y) **do**
    N←getNearestNeighbors(y,k)

4: **foreach** a ∈ A **and** IsMissing(a(y)) **do**
    J1→0, J2→0

6: **foreach** z ∈ N **do**
    M←(Lower approximation+Upper approximation)/2

8:   J1←J1 + M× a(z)
    J2←J1 + M

10: **end**
    if J2>0 **then**

12:   a(y)←(J1/J2)
    else

14:   a(y)←Σ(z)/n
    end if

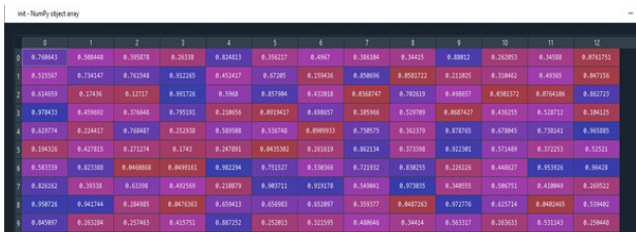16: **end if**
    end

18: **end**
    end

FIGURE 6. Initialize the population positions with random values concerning lower bound and upper bound limit.

TABLE 4. Parameter used for the experiment.

Parameter	Description	Value
T	Number of iteration	100
N	Number of samples	10
K	Number of dimensions	5
Ld	Lower bound	0
Ud	Upper bound	1

and upper bounds for a uniformly distributed random number in the range of 0 to 1. Based on the k neighbours and error rate, calculate the fitness value for the input feature data for N samples. Obtain the global fitness value among the estimated fitness value for the population is shown in the figure 7.

The convergence curves of the fitness values illustrated in Figure 8 reveal that the suggested IHDSSO technique has a superior convergence effect than other optimization models.

Table 5 shows the comparisons of different algorithms. It demonstrates that the Bagging and SMO procedures have nearly identical amounts and both have an accuracy of
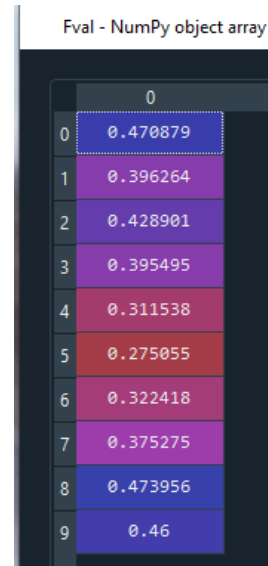

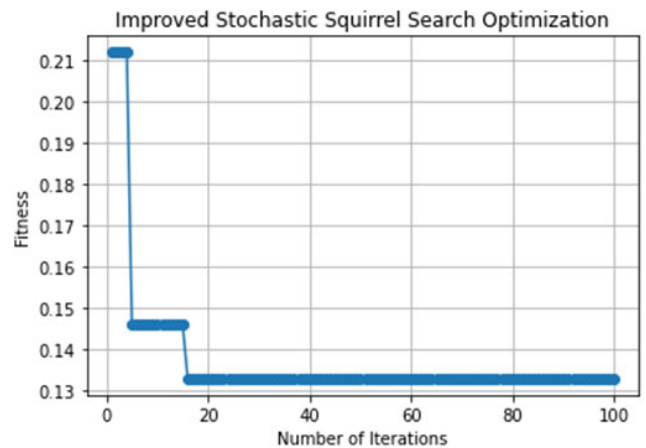**FIGURE 7.** Fitness value for the input features.

FIGURE 8. Convergence of best fitness value for IHDSSO model.

90 percent. The accuracy of Nave Bayes is the lowest. The sensitivity of the Naïve Bayes approach exceeds its accuracy; It tends to diagnose normal people. The neural network is 87 percent accurate. The ICA-KNN is 91 percent accurate. The proposed method is 98 percent more accurate than other methods. The results of comparing the proposed feature selection approach to different methods are shown in Figure 9. The Nearest neighbour (KNN) with Genetic Algorithm(GA) is used for effective classification. Using the Random Forest algorithm, the proposed method utilized stronger and smarter features for classification. As a result, classification accuracy has improved with fewer characteristics, resulting in lower test costs and greater test accuracy in identifying ischemic heart diseases [18].

Furthermore, except for IHDSSO, the OANN(DBMRI-TLBO-ANN) beat all of the analyzed approaches, with 95.41 percent accuracy, 95.74 percent F-score, and 90.76 percent kappa, respectively. The provided IHDSSO model, on the other hand, achieves 98.38 percent accuracy,

TABLE 5. Comparison of efficacy of different algorithms.

Classifiers	Accuracy	Sensitivity	Specificity
Bagging SMO	90.1	91.67	86.21
Naïve Bayes	62.31	50.0	96.55
SMO	90.09	91.67	86.21
Neural Network	87.11	91.67	75.86
ICA-KNN	91.03	91.67	75.86
Proposed IHDSSO	98.38	98.66	98.10

FIGURE 10. Classifier results analysis of sensitivity and specificity.
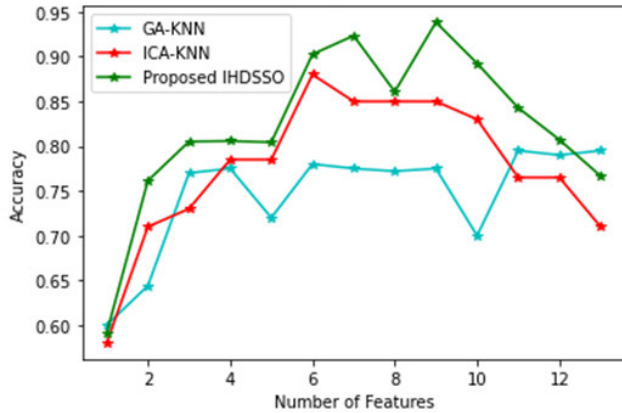
FIGURE 9. A comparison of the accuracy of heart disease diagnosis.

FIGURE 11. Classifier results analysis of accuracy, F-score, and kappa.

98.32 percent F-score, and 96.74 percent kappa, respectively. Table 6 depicts the classification results of several models in terms of specificity, sensitivity, Accuracy, F-Score and Kappa.

Figure 10 shows the categorization models' results in terms of sensitivity and specificity. The Random Tree(RT) model is proven to be poor in the classification process, with a sensitivity and specificity of just 74.41 percent and 71.11 percent, respectively. Furthermore, the J48 classifier model is found to perform somewhat better classification, with a 78.94 and 78.03 percent sensitivity and specificity, respectively. Furthermore, the NBTree model has attempted to outperform previous models by achieving sensitivity and specificity of 80.24 percent and 77.94 percent, respectively. Similarly, with sensitivity and specificity of 81.98 percent and 82.44 percent, the RF model gave reasonable results. Meanwhile, the RBFNetwork model performed admirably, with sensitivity and specificity of 85.19 percent and 81.56 percent, respectively. With a sensitivity and specificity of 97.22 percent and 84.91 percent, respectively, the TLBO-ANN surpassed all other approaches tested. Furthermore, the IHDSSO model beat all other approaches studied, with a sensitivity and specificity of 97.33 and 93.23 percent, respectively, except for OANN. On the other hand, the proposed IHDSSO model achieves maximum sensitivity and specificity of 98.66 and 98.10 percent, respectively.

Figure 11 shows the categorization models' results in terms of kappa, accuracy, and F-score. The RT model is proven to be ineffectual in the prediction process, with limited 72.94 percent accuracy, 75.30 percent F-score, and 45.38 percent kappa value, respectively. Furthermore,
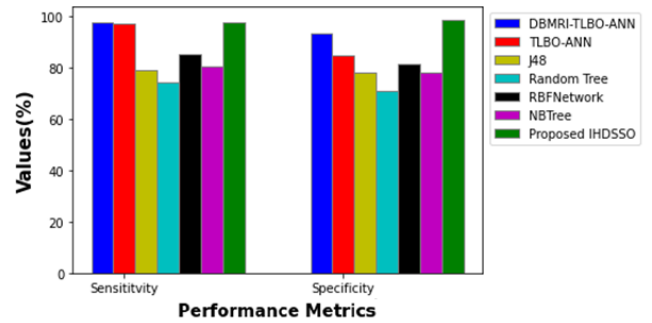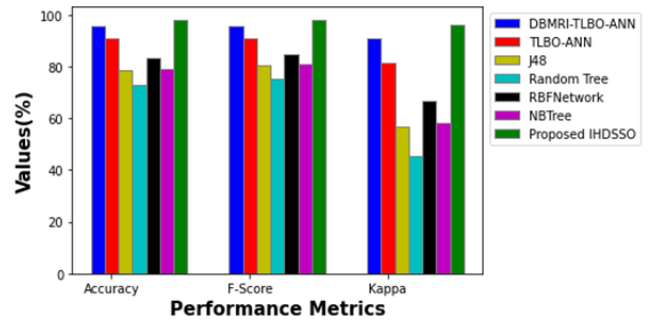
with 78.55 percent accuracy, 80.59 percent F-score, and 56.64 percent kappa values, the J48 classifier model exceeds the others in terms of accuracy, F-score, and kappa values. Furthermore, by obtaining accuracy, F-score, and kappa values of 79.21 percent, 80.97 percent, and 58.06 percent, respectively, the NBTree model sought to beat previous models. With accuracy, F-score, and kappa values of 82.18 percent, 83.93 percent, and 63.95 percent, respectively, the RF model generated reasonable results. With accuracy, F-score, and kappa values of 83.49 percent, 84.66 percent, and 66.81 percent, respectively, the RBFNetwork model has exhibited tolerable performance. With accuracy, F-score, and kappa values of 90.75 percent, 90.91 percent, and 81.59 percent, respectively, the TLBOANN outperformed all other techniques. Furthermore, except for IHDSSO, the OANN beat all of the compared approaches by providing greater 95.41 percent accuracy, 95.74 percent F-score, and 90.76 percent kappa, respectively. The provided IHDSSO model, on the other hand, obtains 98.38 percent maximum accuracy, 98.32 percent F-score, and 96.74 percent kappa, respectively [37].

Finally, a detailed comparative analysis with newly presented models is conducted to further validate the IHDSSO model's improved classification.

Table 7 shows the comparison findings. It is guaranteed that the presented IHDSSO model outperforms all other approaches tested, with a maximum accuracy of 98.38 percent. As a result, it can be used in real-time diagnosis as a classification model. To further validate the efficacy of the suggested model, the AUC of ROC charts were used to compare its performance to that of other models.

TABLE 6. Comparative analysis of existing method with proposed method.

Classifiers	Sensitivity	Specificity	Accuracy	F-score	Kappa
OANN (DBMRI-TLBO-ANN)	97.33	93.23	95.41	95.74	90.76
TLBO-ANN	97.22	84.91	90.75	90.91	81.59
J48	78.94	78.03	78.55	80.59	56.64
Random tree	74.41	71.11	72.94	75.30	45.38
RBFNetwork	85.19	81.56	83.49	84.66	66.81
NBTree	80.24	77.94	79.21	80.97	58.06
Random forest	81.98	82.44	82.18	83.93	63.95
Proposed IHDSSO	98.66	98.10	98.38	98.32	96.74

TABLE 7. Classification accuracies of the proposed model and previous models that used the heart disease dataset.

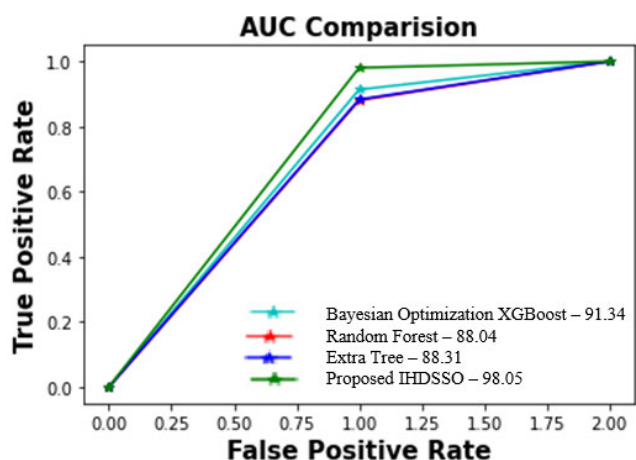| Study (year)	Method	Accuracy(%)
Das et al. (2009)	Neural networks ensembles	89.01
Anooj (2012)	Weighted fuzzy rules	62.35
Samuel et al. (2017)	ANN and fuzzy AHP	91.10
Ali et al. (2019)	Optimized stacked SVM	92.22
Kartik et al. (2020)	Optimized XGBoost on a dataset with OH encoded categorical features	91.80
Proposed IHDSSO	ISSO	98.38

FIGURE 12. AUC charts of Bayesian optimization XGBoost, Random forest, Extra tree, and proposed model.

Figure 12 depict the suggested model, Bayesian optimization XGBoost, Random forest, and Extra tree model ROC charts, respectively. As indicated in the figures, the proposed model's ROC curve AUC is 0.9838, the RF model's AUC is 0.8804, the ET model's AUC is 0.8831, and the Bayesian optimization XGBoost model's AUC is 0.9180. AUC chart outcome reveals the proposed IHDSSO model outperforms Bayesian optimization XGBoost, RF, and ET models in terms of accurcy [38].

The experimental results for different feature selection models demonstrate the superiority of the proposed model due to its ability to handle higher order data, its ability to process an unlimited number of attributes, its best convergence solution, and its ability to produce overall results that strike a balance between exploration and exploitation. The accuracy before optimization was 93% [36], whereas the accuracy after applying the proposed optimization was 98.38%. Thus, the following features are retained namely: "Cp", "restecg", "oldpeak", "Ca", "thal". The discarded features are:"Age". "Sex", "Trestbps", "chol", "Fbs", "Thalach", "Exang", "slope".

VII. CONCLUSION
In the present study, a new approach to the Ischemic Heart Disease Squirrel Search Optimization feature selection algorithm is verified considering the UCI heart disease dataset. The proposed IHDSSO model classifies the most essential features which could be used as a strong predictor for heart disease classification. In the study, we verified that the features like "Cp", "restecg", "oldpeak", "Ca", and "thal" are more essential for the prediction of heart disease. The proposed IHDSSO model in conjunction with a random forest classifier ensured accuracy of over 98.38% and optimal heart disease prediction. The proposed IHDSSO model will be incredibly helpful in supporting healthcare solutions for diagnosing Ischemic heart disease. However, there is a scope for improving the present study in terms of convergence accuracy and convergence speed.

REFERENCES

[1] M. A. Khan, "An IoT framework for heart disease prediction based on MDCNN classifier," *IEEE Access*, vol. 8, pp. 34717–34727, 2020.

[2] M. A. Khan, M. T. Quasim, N. S. Alghamdi, and M. Y. Khan, "A secure framework for authentication and encryption using improved ECC for IoT-based medical sensor data," *IEEE Access*, vol. 8, pp. 52018–52027, 2020.

[3] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques," IEEE Access, vol. 7, pp. 81542–81554, Jan. 2019.

[4] R. Soundharya, D. Cenitta, and R. V. Arjunan, "Information concealment and redemption through data anonymization technique," *J. Adv. Res. Dyn. Control Syst.*, vol. 10, no. 7, pp. 22–26, 2018.

[5] *World Health Organization*. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseas%es-(cvds)

[6] S. C. Yogaamrutha, D. Cenitta, and R. V. Arjunan, "Forecast of coronary heart disease using data mining classification technique," *J. Adv. Res. Dyn. Control Syst.*, vol. 11, no. 4, pp. 25–36, 2019.

[7] D. Cenitta, R. V. Arjunan, and K. Prema, "Missing data imputation using machine learning algorithm for supervised learning," in *Proc. Int. Conf. Comput. Commun. Informat. (ICCCI)*, Jan. 2021, pp. 1–5.

[8] D. Cenitta, R. V. Arjunan, and K. Prema, "Cataloguing of coronary heart malady using machine learning algorithms," in *Proc. 4th Int. Conf. Electr., Comput. Commun. Technol. (ICECCT)*, Sep. 2021, pp. 1–6.

[9] T. S. L. V. Ayyarao, N. S. S. Ramakrishna, R. M. Elavarasan, N. Polumahanthi, M. Rambabu, G. Saini, B. Khan, and B. Alatas, "War strategy optimization algorithm: A new effective Metaheuristic algorithm for global optimization," *IEEE Access*, vol. 10, pp. 25073–25105, 2022.

[10] L. Gao and Y. Ding, "Disease prediction via Bayesian hyperparameter optimization and ensemble learning," *BMC Res. Notes*, vol. 13, no. 1, pp. 1–6, Dec. 2020.

[11] G. Nagarajan and L. D. D. Babu, "A hybrid feature selection model based on improved squirrel search algorithm and rank aggregation using fuzzy techniques for biomedical data classification," *Netw. Model. Anal. Health Informat. Bioinf.*, vol. 10, no. 1, pp. 1–29, Dec. 2021.

[12] M. Jain, V. Singh, and A. Rani, "A novel nature-inspired algorithm for optimization: Squirrel search algorithm," *Swarm Evol. Comput.*, vol. 44, pp. 148–175, Feb. 2019.

[13] Y. Wang and T. Du, "An improved squirrel search algorithm for global function optimization," *Algorithms*, vol. 12, no. 4, p. 80, Apr. 2019.

[14] B. Alatas and H. Bingol, "A physics based novel approach for travelling tournament problem: Optics inspired optimization," *Inf. Technol. Control*, vol. 48, pp. 373–388, Sep. 2019.

[15] B. Alatas and H. Bingol, "Comparative assessment of light-based intelligent search and optimization algorithms," *Light Eng.*, vol. 28, no. 6, pp. 51–59, Dec. 2020.

[16] J. J. Jijesh, "A supervised learning based decision support system for multi-sensor healthcare data from wireless body sensor networks," *Wireless Pers. Commun.*, vol. 116, no. 3, pp. 1795–1813, Feb. 2021.

[17] S. Xu, Z. Zhang, D. Wang, J. Hu, X. Duan, and T. Zhu, "Cardiovascular risk prediction method based on CFS subset evaluation and random forest classification framework," in *Proc. IEEE 2nd Int. Conf. Big Data Anal. (ICBDA)*, Mar. 2017, pp. 228–232.

[18] J. Nourmohammadi-Khiarak, M.-R. Feizi-Derakhshi, K. Behrouzi, S. Mazaheri, Y. Zamani-Harghalani, and R. M. Tayebi, "New hybrid method for heart disease diagnosis utilizing optimization algorithm in feature selection," *Health Technol.*, vol. 10, no. 3, pp. 667–678, May 2020.

[19] F. A. M. Al-Yarimi, N. M. A. Munassar, M. H. M. Bamashmos, and M. Y. S. Ali, "Feature optimization by discrete weights for heart disease prediction using supervised learning," *Soft Comput.*, vol. 25, no. 3, pp. 1821–1831, Feb. 2021.

[20] M. A. Khan and F. Algarni, "A healthcare monitoring system for the diagnosis of heart disease in the IoMT cloud environment using MSSO-ANFIS," *IEEE Access*, vol. 8, pp. 122259–122269, 2020.

[21] T. Zheng and W. Luo, "An improved squirrel search algorithm for optimization," *Complexity*, vol. 2019, pp. 1–31, Jul. 2019.

[22] M. Kader, "Comparative study of five metaheuristic algorithms for team formation problem," in *Human-Centered Technology for a Better Tomorrow*. Cham, Switzerland: Springer, 2022, pp. 133–143.

[23] C. A. Subasini, S. P. Karuppiah, A. Sheeba, and S. Padmakala, "Developing an attack detection framework for wireless sensor network-based healthcare applications using hybrid convolutional neural network," *Trans. Emerg. Telecommun. Technol.*, vol. 32, no. 11, Nov. 2021, Art. no. e4336.

[24] M. S. Sanaj and P. M. Joe Prathap, "Nature inspired chaotic squirrel search algorithm (CSSA) for multi objective task scheduling in an IAAS cloud computing atmosphere," *Eng. Sci. Technol., Int. J.*, vol. 23, no. 4, pp. 891–902, Aug. 2020.

[25] A. Muneer, S. M. Taib, S. M. Fati, A. O. Balogun, and I. A. Aziz, "Optimized stacked autoencoder for IoT enabled financial crisis prediction model," *Comput., Mater. Continua*, vol. 71, no. 1, pp. 1079–1094, 2022.

[26] V. P. Sakthivel and P. D. Sathya, "Single and multi-area multi-fuel economic dispatch using a fuzzified squirrel search algorithm," *Protection Control Modern Power Syst.*, vol. 6, no. 1, pp. 1–13, Dec. 2021.

[27] M. Dhaini and N. Mansour, "Squirrel search algorithm for portfolio optimization," *Expert Syst. Appl.*, vol. 178, Sep. 2021, Art. no. 114968.

[28] P. A. Moreno-Sanchez, "Development of an explainable prediction model of heart failure survival by using ensemble trees," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Dec. 2020, pp. 4902–4910.

[29] P. Ghosh, S. Azam, M. Jonkman, A. Karim, F. M. J. M. Shamrat, E. Ignatious, S. Shultana, A. R. Beeravolu, and F. D. Boer, "Efficient prediction of cardiovascular disease using machine learning algorithms with relief and LASSO feature selection techniques," *IEEE Access*, vol. 9, pp. 19304–19326, 2021.

[30] J. J. Gabriel and L. J. Anbarasi, "Evolutionary computing-based feature selection for cardiovascular disease: A review," in *Proc. Int. Virtual Conf. Ind. 4.0*. Cham, Switzerland: Springer, 2021, pp. 47–56.

[31] P. Anuradha and V. K. David, "Feature selection and prediction of heart diseases using gradient boosting algorithms," in *Proc. Int. Conf. Artif. Intell. Smart Syst. (ICAIS)*, Mar. 2021, pp. 711–717.

[32] K. V. V. Reddy, I. Elamvazuthi, A. A. Aziz, S. Paramasivam, H. N. Chua, and S. Pranavanand, "Heart disease risk prediction using machine learning classifiers with attribute evaluators," *Appl. Sci.*, vol. 11, no. 18, p. 8352, Sep. 2021.

[33] Cleveland. *UCI Heart Disease Dataset*. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/heart+disease

[34] S. Ulianova. *Kaggle Heart Disease Dataset*. [Online]. Available: https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-datas%et

[35] S. Akyol and B. Alatas, "Plant intelligence based metaheuristic optimization algorithms," *Artif. Intell. Rev.*, vol. 47, no. 4, pp. 417–462, 2017.

[36] D. Cenitta, R. V. Arjunan, and K. Prema, "Ischemic heart disease multiple imputation technique using machine learning algorithm," *Engineered Sci.*, to be published.

[37] R. T. Selvi and I. Muthulakshmi, "An optimal artificial neural network based big data application for heart disease diagnosis and classification model," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 6, pp. 6129–6139, 2021.

[38] K. Budholiya, S. K. Shrivastava, and V. Sharma, "An optimized XGBoost based diagnostic system for effective prediction of heart disease," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 7, pp. 4514–4523, Jul. 2022.

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