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A Hybrid Approach to Cardiovascular Disease Prediction Using Support Vector Machine and Enhanced Teaching Learning-Based Optimization

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Abstract**—** Accurate prediction models are needed to prevent and treat cardiovascular diseases (CVDs), a global health threat. This study recommends using SVM and ETLBO to improve CVD prediction accuracy. Age, gender, cholesterol levels, blood pressure, type of chest pain, electrocardiogram (ECG) results, and other risk variables are collected to start the study. Feature selection methods discover the most valuable predictors. SVM is the base classifier because it can handle complex and non-linear data connections. SVM requires manual hyperparameter adjustment, which is time-consuming and inefficient. The ETLBO technique automatically optimizes SVM hyperparameters to increase performance. The hybrid strategy is tested on a large CVD dataset against classic SVM and other optimization methods. The hybrid strategy surpasses SVM and other optimization strategies in accuracy, sensitivity, and specificity. In conclusion, the hybrid SVM-ETLBO methodology for CVD prediction outperforms classic SVM and other optimization methods.

Keywords**—** Cardiovascular Disease Prediction, Lorenz Chaotic Map, Support Vector Machine, Teaching Learning Based Optimization.

I. INTRODUCTION

Background of the Study

Cardiovascular disease (CVD) poses a pervasive and substantial global health burden, leading to many disabilities and premature fatalities. The year 2015 witnessed an alarming estimate of 422.7 million reported cases of CVD, resulting in approximately 17.92 million deaths. [10] According to the WHO, adequate, coordinated preventive measures can prevent one-third of all CVD mortality. Concurrently, efforts have been dedicated to developing predictive models for CVD to mitigate the impact of this global health issue.

[12] The study entitled "Machine Learning Techniques for Heart Disease Prediction: A Comparative Study and Analysis") highlights the importance of the different machine learning algorithms in processing medical data for CVD prediction.

The results of the study show that one of the top performing algorithms for CVD prediction is the Support Vector Machine (SVM), alongside other algorithms such as Logistic Regression, Naïve Bayes, Random Forest, and Artificial Neural Network, hence the chosen classification algorithm for this study [20]. Due to its ability to handle complex and nonlinear data relationships, Support Vector Machine (SVM) has been extensively utilized in medical research. However, the performance of SVM is highly dependent on selecting appropriate hyperparameters, which can be a complex undertaking and affects the model's accuracy [21]. To overcome this limitation, optimization techniques have been employed to automate the process of hyperparameter tuning and boost the efficacy of SVM. Teaching Learning-Based Optimization (TLBO) is one such optimization algorithm that simulates the teaching and learning processes observed in a classroom. TLBO has demonstrated promise in several optimization problems, including the optimization of machine learning algorithm parameters. To improve the accuracy of CVD prediction models, the proponents will employ an Enhanced Teaching Learning-Based Optimization (ETLBO) hybrid approach that combines SVM and an enhanced variant of Teaching Learning-Based Optimization (TLBO). The integration of ETLBO aims to automatically optimize the SVM hyperparameters, eradicating the need for manual tuning and enhancing the predictive model's overall performance.

Statement of the Problem

The algorithms to be utilized for predicting cardiovascular disease using a Support Vector Machine (SVM) and Enhanced Teaching Learning-Based Optimization has several drawbacks. The following assertions are examined in this study:

1. There's difficulty in selecting kernel functions and hyperparameters in Support Vector Machine.
2. Teaching-Learning-Based Optimization suffers from premature convergence and entrapment in local optima.
3. The Teaching-Learning-Based Optimization has an inherent bias in the teaching and learning phase that may result in exploitation of the optimization problem.

Objectives of the Study

The general objective is to improve Teaching Learning-Based Optimization and Support Vector Machine for cardiovascular disease prediction in terms of Accuracy, Specificity, and Sensitivity. Specific objectives include (1) Use the Enhanced Teaching-Learning-Based Optimization algorithm to optimize the hyperparameters of the Support Vector Machine and (2) apply Lorenz Chaotic Map in the Teaching Phase and Manhattan Distance to Learning Phase to solve premature convergence and entrapment in local optima, this would also solve the bias in the teaching and learning phase of the base algorithm.

Significance of the Study

This study aims to offer a new perspective on how to improve Cardiovascular Disease Prediction using a hybrid of Support Vector Machine (SVM) and Enhanced Teaching Learning-Based Optimization. The study will most likely benefit the following:

Medicine-related students who are interested in Computer Science. Information on cardiovascular disease prediction with machine learning would be a great additional knowledge to them.

Future researchers. These people who intend to approach cardiovascular disease prediction with machine learning will be able to utilize this study as a related literature to build their overview and methodology.

Scope and Delimitations

This research will only focus on cardiovascular disease prediction using Support Vector Machine and the Enhanced Teaching-Learning-Based Optimization Algorithm.

The dataset will only have the following features: age, gender, cholesterol levels, blood pressure, type of chest pain, electrocardiogram (ECG) results, and the presence or absence of cardiac disease.

The research will not extend to any diseases other than the one mentioned above. The proponents will not utilize any algorithm other than Support Vector Machine and Enhanced Teaching-Learning-Based algorithm.

II. REVIEW OF RELATED LITERATURE

Cardiovascular Disease Prediction

[9] There is an increase in the number of people suffering from cardiovascular disease. An estimated 17 million people die every year because of cardiovascular disease. Unfortunately, it's challenging to detect a cardiovascular disease at an early stage because there are a lot of factors to consider. Thus, there is a necessity for medical diagnostic support systems which can aid medical practitioners in the diagnostic process. [13] Many have tried to utilize data mining in predicting, treating, and analyzing cardiovascular disease datasets. Machine learning algorithms such as logistic regression, neural networks, ensemble algorithms, and decision trees have been used in this field. Some of the research about CVD prediction are stated below. In a study conducted by [27] Reddy et al (2020), they introduced an approach incorporating attribute evaluators that is based on machine learning.

The researchers employed ten diverse machine learning models, including Bayesian-based models, tree-based models, and rules-based models. Utilizing all of the Cleveland dataset's attributes along with the optimal attributes identified by three attribute evaluators, they aimed to accomplish accurate prediction of cardiovascular disease.

When using the complete set of attributes, sequential minimal optimization obtained an accuracy of 85.148%, whereas accuracy increased to 86.468% when using the optimal attributes. The proponents of this research seek to improve the overall accuracy of CVD prediction using SVM as a machine learning classifier enhanced with a modified Teaching Learning Based Optimization.

Support Vector Machine

Support Vector Machines (SVM) have attracted a great deal of interest in the fields of machine learning and pattern recognition as a result of their ability to manage both linear and nonlinear classification and regression tasks effectively.

Numerous studies have examined the capabilities, developments, and applications of SVM, highlighting their prospective strengths and weaknesses. [35]

According to Tan and Wang (2004), SVMs are based on the concept of structural risk minimization (SRM) , which demonstrates that generalization errors are constrained by the sum of training errors and a term that depends on the Vapnik-Chervonenkis (VC) dimension of the learning systems.

By minimizing this upper bound, one can obtain high generalization performance. In addition, unlike other machine learning techniques, the generalization errors of SVMs are not proportional to the input dimensionality of the problem, but rather to the data separation margin.

This explains why SVMs can perform well even when presented with many inputs. [36] In a study conducted by Cervantes et al. (2020), it was determined that despite the SVM's generalization capability and many advantages, it has some very pronounced weaknesses, including the selection of parameters, algorithmic complexity that affects the training time of the classifier in large data sets, development of optimal classifiers for multi-class problems, and the performance of SVMs in unbalanced data sets.

Teaching Learning Based Optimization

Teaching Learning-Based Optimization (TLBO) algorithm is a population-based optimization algorithm inspired by classroom instruction and learning.

[40] Rao et al. (2011) first introduced it in 2011 as a metaheuristic optimization algorithm capable of solving a variety of optimization issues.

The TLBO algorithm combines the students' capability of exploration with the teacher's capability of exploitation to find improved solutions.

It employs a cooperative learning approach to modify solutions adaptively and converge on the optimal solution.

Despite the fact that the TLBO algorithm has been demonstrated to have competitive exploration capability and rapid convergence speed, it is still possible for it to become trapped in the phenomena of local convergence.

[6] Consequently, numerous modifications have been made to the variants of TLBO in order to improve their exploitation and exploration capabilities (Zou & Xu, 2018). TLBO provides a promising solution by utilizing its population-based optimization strategy to efficiently seek for the optimal hyperparameters and margin settings in SVM.

By exchanging information iteratively between teacher and student solutions, TLBO identifies the optimal configuration for SVM, resulting in improved classification accuracy and generalization performance. Hence, the algorithm of choice in this hybrid approach.

III. THEORETICAL FRAMEWORK

Existing Teaching Learning-Based Optimization

First proposed by [40] Rao et al. (2011) teaching learning based optimization (TLBO) is a population-based heuristic stochastic swarm intelligent system that simulates the teaching-learning process in a classroom.

Similar to a conventional evolutionary algorithm, TLBO employs techniques of iterative evolution.

Unlike standard evolutionary algorithms and swarm intelligence algorithms, each phase of TLBO's iterative computation process implements an iterative learning operation.

Teaching Phase

1. The algorithm assesses the fitness or objective value of every solution (student) in the population.
2. The algorithm identifies as the teacher the solution (student) with the highest fitness value.
3. Through performing a teaching operation, the teacher imparts its knowledge to the remainder of the population.

Learning Phase

1. Every student receives and assimilates the knowledge imparted by the teacher.
2. Each student modifies their own solution based on the knowledge they've gained.
3. The students' updated solutions replace their prior ones in the population.

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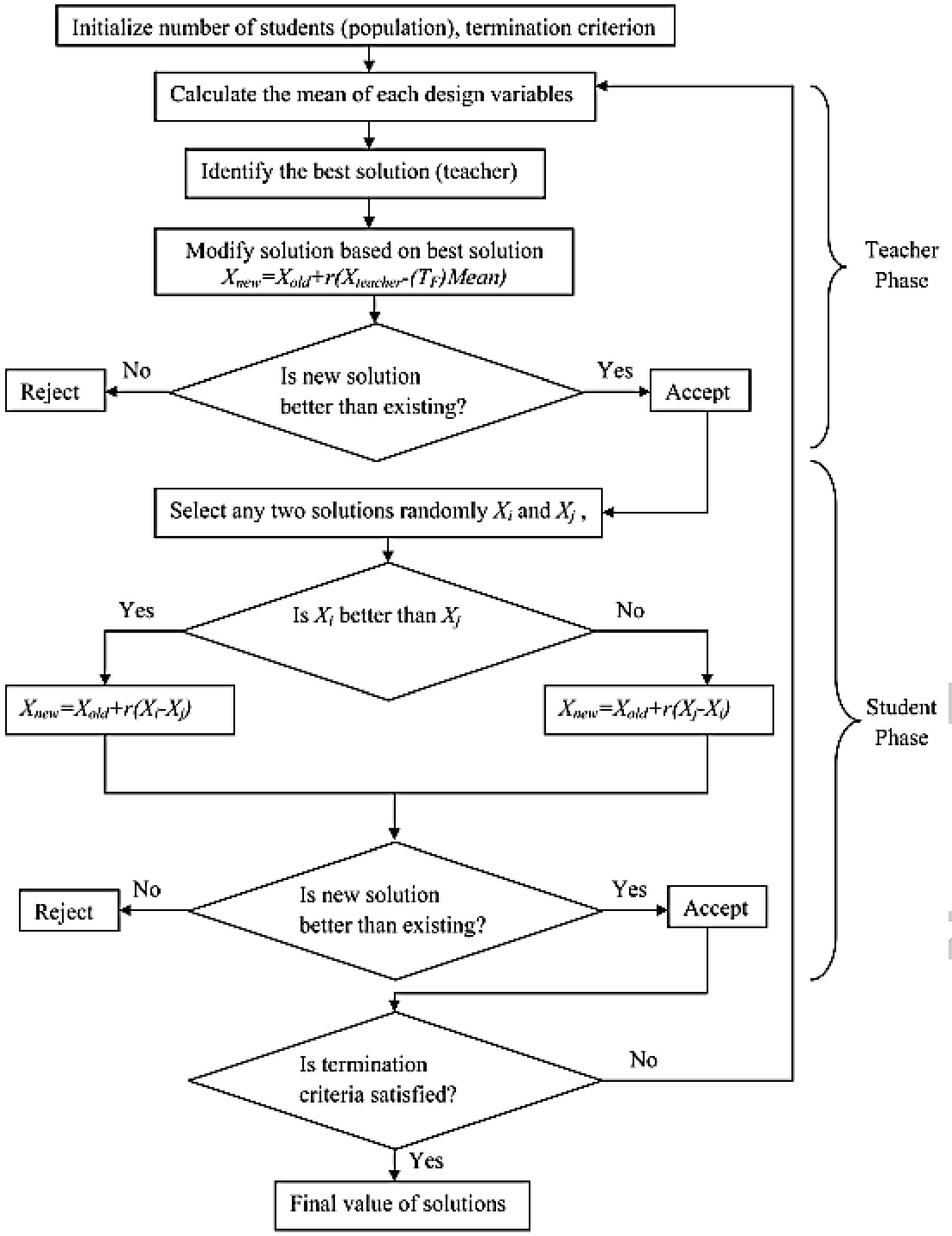

Fig 1. *Flowchart for Existing TLBO*

Support Vector Machine

SVM is a supervised machine learning method applicable to classification and regression problems. The core concept of support vector machines is to define a boundary (or hyperplane) that divides the data into distinct classes or groups. The boundary is chosen to maximize the margin, which is the distance between the boundary and the closest data point from each class. It has been utilized in numerous applications, such as text classification, image classification, bioinformatics, and face recognition.

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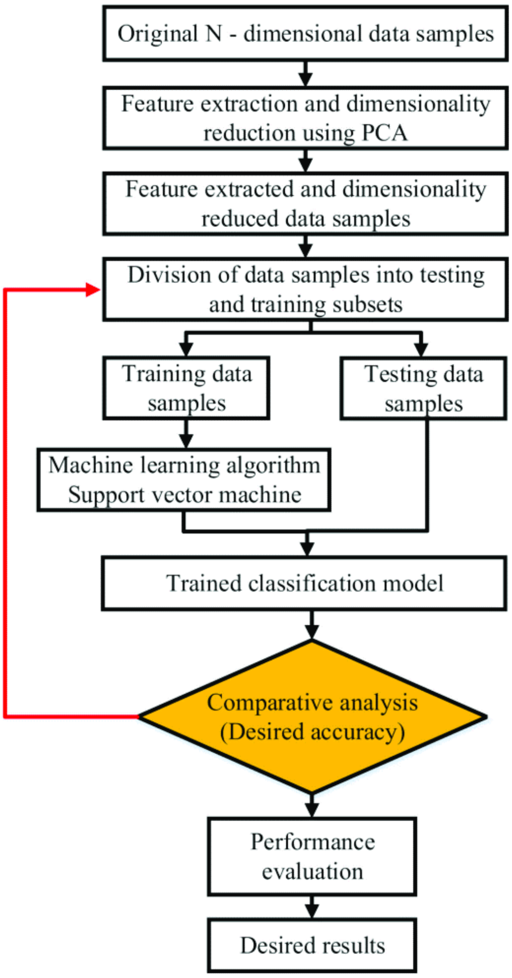

***Fig 2.** Flowchart for Support Vector Machine*

Proposed Enhanced Teaching Learning Based Optimization

Enhanced Teaching Learning-Based Optimization (ETLBO) is a sophisticated variant of the Teaching Learning-Based Optimization (TLBO) algorithm that employs additional performance-enhancing techniques. In ETLBO, the Lorenz chaotic map is used to improve the teaching phase, while the Manhattan distance is used to measure similarity in the learning phase.

Lorenz Chaotic Map

[38] The Lorenz is a three-dimensional dynamical chaos map. In 1963, famous physicist Edward Lorenz invented the coupled differential equation. Lorenz chaos sequences form the Lorenz system's chaotic attractor. The Lorenz system plots the Butterfly-shaped attractor. Atmospheric convection inspired the chaotic system.

A simple formula describes the system. ETLBO uses the Lorenz chaotic map to help teachers educate. Lorenz chaotic maps generate chaotic and unexpected values. The ETLBO method uses the chaotic Lorenz map to add unpredictability and curiosity to the teaching phase, allowing a more diverse solution space discovery. This increased teaching phase helps the algorithm avoid local optimums and identify superior solutions.

Manhattan Distance

[39] The Manhattan distance is used to determine the absolute difference between two sets of coordinates. The following formula is employed:

$$d_{ij} = \sum_{k=1}^{n} \left| x_{ij} - y_{ik} \right|$$

***Fig 3.** Manhattan Distance Formula*

Where d is the distance between i and j,i as the cluster data center, j data on the attribute, k symbol of each data, n the amount of data,n the amount of data, xik is the data at the cluster center to k, and yjk is the data on each data to k.

ETLBO uses Manhattan distance to compare solutions during learning. The Manhattan, L1, or taxicab distance evaluates the absolute differences between two solutions' properties. ETLBO uses Manhattan distance to compare two solutions based on attribute differences. This measure finds solutions that are closer in solution space and may complement one other.

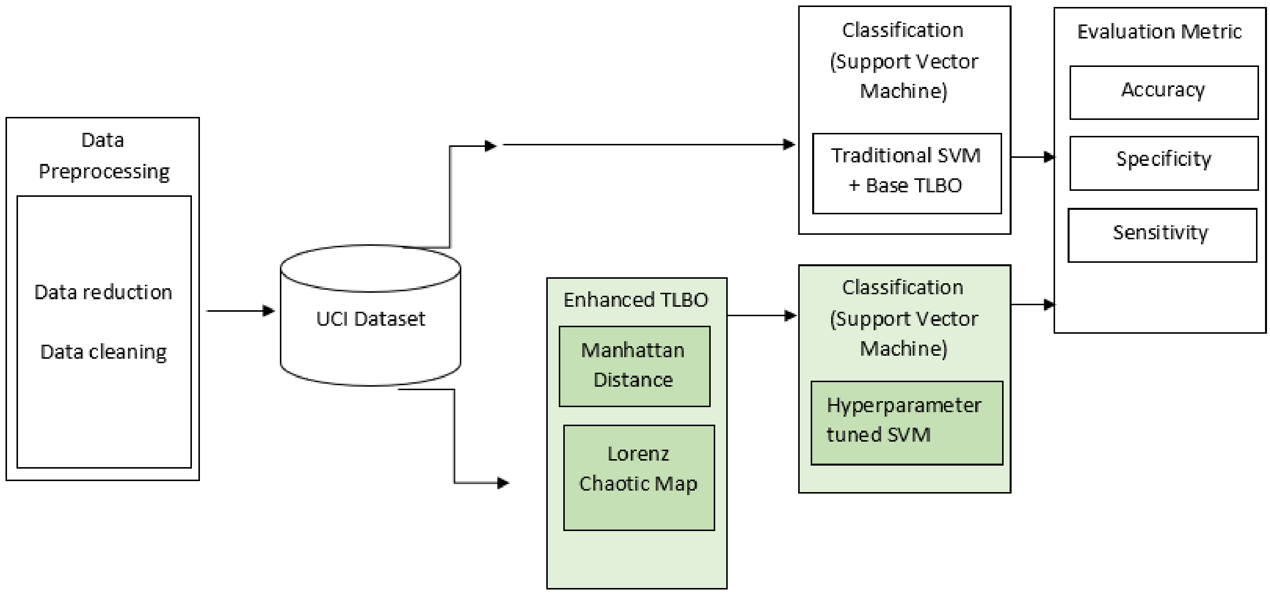

Fig 4. *Proposed Framework for TLBO +SVM Hybrid*

IV. MATERIALS AND METHODOLOGY

Dataset

Genetics, lifestyle, and medical history affect cardiovascular disease. Large-scale data analysis can uncover hidden patterns and relationships, helping researchers understand this disease's complexity. This dataset describes a publicly available Kaggle heart disease dataset and its research uses.The heart disease dataset includes 14 patient-specific features from several clinical sources. These include age, gender, cholesterol, blood pressure, kind of chest discomfort, electrocardiogram (ECG) readings, and cardiac illness. Over 300 observations give the dataset a large scientific sample.

Data Pre-processing

Pre-processing this dataset improves its quality and prepares it for machine learning modeling. Data cleansing, feature scaling, categorical data handling, feature selection, balancing, and splitting are pre-processing stages. Data cleaning involves finding missing, duplicate, and incorrect values. This dataset had no missing values, but duplicated and incorrect records were eliminated to avoid bias. Feature scaling normalizes numerical features to the same scale. MinMaxScaler from scikit-learn normalized numerical features for this dataset. One-hot or label encoding is used to handle categorical data as numerical data. Gender and smoking behaviors were encoded using one-hot encoding in this dataset. Statistical approaches or feature importance algorithms are used to choose the most important dataset features. ETLBO selected features for analysis in this dataset. Splitting the dataset into training and testing sets tests the model on unseen data. Stratified sampling divided this dataset into a training set (80%) and a testing set (20%).

System Implementation

Hyperparameter bounds start the algorithm. The limitations limit created hyperparameters. Each member of a random population represents a set of ideal hyperparameters and accuracy, which are initialized to their default values. The core optimization cycle repeats. Each iteration updates all population hyperparameters. Education does this. The teaching phase computes the population-wide mean hyperparameter values, reflecting the "teaching individual." A chaotic term based on the teaching factor and the difference between the teaching individual's hyperparameter values and the current values modifies each individual's hyperparameters. This disorder allows solution space exploration in optimization. Algorithms learn stochastically. Random numbers select two population members. "Distance" is Manhattan distance between hyperparameter values. Learning factor, distance term, and random numbers update the individual's hyperparameters. This phase increases solution space utilization. After updating each person, hyperparameters are reduced for practicality. Classification accuracy is used to evaluate each person. Accuracy wins. A better individual will update optimal hyperparameters and precision. Save the best person's hyperparameters and accuracy. To sustain population variation, the best individual's hyperparameters replace the first's. Core optimization loop iterates till maximum. Optimization yields hyperparameters and precision. Teaching and learning methods make the improved TLBO algorithm resilient hyperparameter optimization. Learning leverages potential, whereas teaching creates chaos to explore solution space. The algorithm optimizes hyperparameters. The method optimizes machine learning and other parameters.

Python Libraries

1. NumPy: Python's NumPy library performs several array-based mathematical computations. Python's NumPy library provides efficient array and matrix calculation data structures. Additionally, it supports a wide range of complex mathematical operations on arrays and matrices.
2. Pandas: Python's Pandas package provides versatile and efficient data structures for labeled and relational data. It's meant to simplify the process. User experience improvement through data processing. To provide a core Python data analysis component.
3. Sci-kit learn: Scikit-Learn is one of the most widely used Python libraries for machine learning. Scikit-Learn implements machine learning techniques in a reliable and easy way. It was an open-source project. This paper will provide emphasis on Scikit-Learn's role in efficient and effective machine learning workflows.

Evaluation Metrics

In numerous disciplines, including statistics, machine learning, and healthcare, accuracy, specificity, and sensitivity are frequently used as performance metrics. These metrics are used to assess the effectiveness of classification models and diagnostic tests.

Accuracy examines a classification model or diagnostic test's complete validity. It is the percentage of correctly classified instances. A model or test is accurate if it correctly identifies positive and negative cases. When classifications are unequal or misclassification costs vary, precision may not be enough.

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

Specificity evaluates how well a classification model or diagnostic tool can identify negative cases. It is the ratio of true negatives (properly detected negatives) to true negatives and false positives (incorrectly identified negatives). Specificity reduces false positives and maximizes true negatives when erroneous positives are costly.

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

Sensitivity (sometimes called Recall or True Positive Rate) assesses a classification model or diagnostic instrument's accuracy in identifying positive instances. It is the ratio of true positives to false negatives. Sensitivity reduces false negatives and maximizes true positives when false negatives are costly.

$$sensitivity = TP / (TP + FN)$$

V. RESULTS AND DISCUSSION

Comparison of Proposed Method to Existing Methods

Table 1 compares the performance metrics of existing methods, namely PSO (Particle Swarm Optimization), OlexGA (Orthogonal Lexicographic Genetic Algorithm), and D-ACO (Discrete Ant Colony Optimization), with those of the proposed method ETLBO-SVM (Enhanced Teaching Learning-Based Optimization combined with Support Vector Machine). The evaluated metrics include the number of features, sensitivity, specificity, and precision.

Table 1. *Comparison of different Methods to ETLBO-SVM with the Performance Metrics (No. of Features, Sensitivity, Specificity, Accuracy)*

Performance Metrics	**Existing Methods**			**Proposed Method**
	PSO	OlexGA	D-ACO	ETLBO-SVM
No. of Features	14	14	14	7
Sensitivity	88	80	96	93.57

Specificity	80	66.66	93.3	94.06
Accuracy	85	75	95	92.37

In terms of sensitivity, specificity, and precision, the results indicate that the D-ACO method outperforms extant methods. However, the proposed ETLBO-SVM method achieves competitive results across all metrics, attaining a high level of sensitivity, specificity, and accuracy with a smaller feature set. This indicates that the ETLBO-SVM method can provide an effective and precise approach for the classification task at hand. The generalizability and robustness of the proposed method could be elucidated through additional evaluation and comparison with additional data sets.

Comparison of SVM with TLBO and ETLBO Features

Using TLBO features, the SVM algorithm obtained an accuracy of 85 percent, according to the findings. However, when ETLBO features were implemented, accuracy increased to 92.37 percent. This enhancement demonstrates the efficiency of the ETLBO feature extraction technique in enhancing the classification performance of the SVM algorithm. Refer to the table below Table 2.

Table 2. *Comparison of SVM with TLBO & ETLBO Feature selection*

Classification Algorithm	**With Base TLBO Features (%)**			**With ETLBO Features (%)**		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
SVM	85	86.8	82.5	92.37	93.57	94.06

ETLBO includes higher sensitivity from 86.8% to 93.57%. ETLBO characteristics helped the SVM algorithm capture positive cases, increasing sensitivity. ETLBO features boosted negative instance specificity from 82.5% to 94.06%. ETLBO features improve classification of negative cases. Feature extraction enhances classification accuracy and machine learning algorithm performance. ETLBO optimization can increase classification algorithm accuracy and reliability for researchers and practitioners. ETLBO features can be assessed in various classification methods and datasets.

Comparison SVM-ETLBO Accuracy with other Classification Techniques

The dataset containing cardiovascular disease-related features is analyzed using the SVM with increased TLBO hybridization. Table 5.3 compares the results to other studies that used alternative Classification Techniques on the same data set.

We analyzed a broad dataset of multi-author textual materials. This study uses ETLBO, Naive Bayes (NB), ANN Ensemble, Learning Vector Quantization (LVQ), Decision Trees (DT), and Support Vector Machines (SVM) for classification. GA and ANN hybrid systems were examined. Fig. 5 Our study (Romero & Ruazol) combined Enhanced Teaching Learning Based Optimization (ETLBO) and Support Vector Machines (SVM) to achieve 92.37 percent accuracy. This approach accurately recognizes writers by textual characteristics. Vembandasamy et al. had 86.42 percent accuracy with the NB approach, whereas Medhekar had 88.96 percent.Das et al. used an ANN Ensemble model for 89.01% accuracy. Chen et al. achieved 80% accuracy with ANN LVQ. Sabarinathan and Sugumaran achieved 85% accuracy using DT. Patel et al. and Wiharto et al. had lower accuracy rates of 56.76 and 61.86 percent, respectively, using DT and SVM.

Author	Classification Technique	Accuracy
Romero & Ruazol	ETLBO and SVM	92.37%
Vembandasamy et al.	NB	86.4198%
Medhekar et al.	NB	88.96%
Das et al.	ANN Ensemble	89.01%
Chen et al.	ANN LVQ	80%
Sabarinathan and Sugumaran	DT	85%
Patel et al.	DT	56.76%
Wiharto et al.	SVM	61.86%
Khateeb and Usman	NB, KNN, DT and bagging technique	79.20%
Pouriyeh et al.	NB, DT, MLP, KNN, SCRL, RBF, SVM, bagging, boosting and stacking	84.81%
Amin et al.	ANN and Genetic Algorithm hybrid system	89%
Venkatalakshmi and Shivsankar	NB and DT	85.03%
Palaniappan and Awang	DT, NB and ANN	86.53%
Ghumbre et al.	SVM and Radial Basis Function	86.42%

Fig 5. *Comparison of SVM & ETLBO to other studies.*

Using a combination of NB, KNN, DT, and packaging, Khateeb and Usman achieved an accuracy of 79.20%. Pouriyeh et al. utilized multiple techniques, such as NB, DT, MLP, KNN, SCRL, RBF, SVM, bagging, boosting, and stacking, to achieve an accuracy of 84.81 percent. Amin et al. employed a hybrid ANN and GA system with an 89% accuracy rate. Using NB and DT techniques, Venkatalakshmi and Shivsankar obtained an accuracy of 85.03 percent. Palaniappan and Awang utilized DT, NB, and ANN to achieve an accuracy of 86.53 percent.

In summary, we investigated and contrasted a variety of CVD classification techniques. Enhanced Teaching Learning Based Optimization (ETLBO) in conjunction with Support Vector Machines (SVM) yielded the highest accuracy of 92.37 percent in our study, as represented by Romero and Ruazol.

This finding demonstrates that this approach accurately predicts cardiovascular disease. When selecting an appropriate classification technique, it is essential to take into account the specific characteristics of the dataset and the nature of the texts being analyzed. Future research can investigate combinations of various models or the use of deep learning techniques to further improve CVD prediction accuracy.

V. CONCLUSION AND RECCOMENDATIONS

Conclusion

Classification techniques are vital for accurate data categorization and prediction. This study compares the performance of existing methods (PSO, OlexGA, and D-ACO) with the proposed ETLBO-SVM (Enhanced Teaching Learning-Based Optimization combined with Support Vector Machine) approach. The evaluation criteria include the number of features, sensitivity, specificity, and accuracy. The SVM algorithm with ETLBO features demonstrates significant improvement compared to TLBO features. ETLBO-SVM achieves higher accuracy (92.37%), sensitivity (93.57%), and specificity (94.06%) compared to TLBO features. ETLBO-SVM performs well with a sensitivity of 93.57%. ETLBO-SVM also outperforms other methods in terms of specificity (94.06%) and accuracy (92.37%). The comparative analysis reveals the effectiveness of the proposed ETLBO-SVM method in enhancing classification performance. It achieves competitive results in terms of sensitivity, specificity, and accuracy, while utilizing a smaller feature set. ETLBO-SVM demonstrates its potential as an accurate and efficient classification technique.

Recommendations

Further research should explore the generalizability and robustness of ETLBO-SVM across different datasets and classification tasks. Additionally, the combination of advanced optimization techniques and machine learning algorithms, as demonstrated by ETLBO-SVM, holds promise for improving classification accuracy and reliability in various domains. This study's findings contribute to the development of classification techniques and encourage further investigation of optimization-based machine learning algorithms.

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REFERENCES

[1] Wu, D., Jia, H., Abualigah, L., Xing, Z., Zheng, R., Wang, H., & Altalhi, M. (2022). Enhance Teaching-Learning-Based Optimization for Tsallis-Entropy-Based Feature Selection Classification Approach. Processes,10(2),360. https://doi.org/10.3390/pr10020360

[2] Yang, X., Peng, Y., Su, X., Yang, Z., Ding, C., & Yang, X. (2022). Improving teaching–learning-based-optimization algorithm by a distance-fitness learning strategy. Knowledge Based Systems, 257, 108271. https://doi.org/10.1016/j.knosys.2022.108271

[3] M, Manonmani., & Balakrishnan, S. (2020). Feature Selection Using Improved Teaching Learning Based Algorithm on Chronic Kidney Disease Dataset. Procedia Computer Science, 171, 1660–1669. https://doi.org/10.1016/j.procs.2020.04.178

[4] Wu, D., Wang, S., Liu, Q., Abualigah, L., & Jia, H. (2022). An Improved Teaching-Learning-Based Optimization Algorithm with Reinforcement Learning

Strategy for Solving Optimization Problems. Computational Intelligence and Neuroscience,2022,1–24. https://doi.org/10.1155/2022/1535957

[5] Ali, L., Niamat, A., Khan, J. A., Golilarz, N. A., Xingzhong, X., Noor, A., Nour, R., & Bukhari, S. A. C. (2019). An Optimized Stacked Support Vector Machines Based Expert System for the Effective Prediction of Heart Failure. IEEE Access, 7,54007–54014. https://doi.org/10.1109/ACCESS.2019.2909969

[6] Zou, F., Chen, D., & Xu, Q. (2019). A survey of teaching–learning-basedoptimization. Neurocomputing,335,366–383. https://doi.org/10.1016/j.neucom.2018.06.076

[7] Mohan, L., Pant, J., Suyal, P., & Kumar, A. (2020). Support Vector Machine Accuracy Improvement with Classification. 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN). https://doi.org/10.1109/cicn49253.2020.9242572

[8] Fontecha, J., Calvo, M. L., Juárez, M., Gil, A., & Martínez-Vizcaíno, V. (2019). Milk and Dairy Product Consumption and Cardiovascular Diseases: An Overview of Systematic Reviews and Meta-Analyses. Advances in Nutrition, 10(suppl_2), S164–S189. https://doi.org/10.1093/advances/nmy099

[9] Smith, S. C., Jackson, R., Pearson, T. A., Fuster, V., Yusuf, S., Faergeman, O., Wood, D. A., Alderman, M. H., Horgan, J., Gerstein, H. C., Hunn, M., & Grundy, S. M. (2004). Principles for National and Regional Guidelines on Cardiovascular Disease Prevention. Circulation, 109(25), 3112–3121. https://doi.org/10.1161/01.cir.0000133427.35111.67

[10] World Health Organization. Joint WHO/FAO Expert Consultation on Diet, Nutrition and the Prevention of Chronic Diseases, Report No. 91, 2002.

[11] Janosi,Andras,Steinbrunn,William, Pfisterer,Matthias, and Detrano,Robert. (1988). Heart Disease. UCI Machine Learning Repository. https://doi.org/10.24432/C52P4X.

[12] Katarya, R., Meena, S.K. Machine Learning Techniques for Heart Disease Prediction: A Comparative Study and Analysis. Health Technol. 11,87–97(2021). https://doi.org/10.1007/s12553-020-00505-7

[13] Aljanabi, M., Qutqut, M. H., & Hijjawi, M. (2018). Machine Learning Classification Techniques for Heart Disease Prediction: A Review. ResearchGate. https://doi.org/10.14419/ijet.v7i4.28646

[14] K. Vembandasamy, R. Sasipriya, and E. Deepa, “Heart diseases detection using naive bayes algorithm,” International Journal of Innovative Science, Engineering & Technology, vol. 2, no. 9, pp. 441–444, 2015.

[15] D. Medhekar, M. Bote, and S. Deshmukh, “Heart disease prediction system using naive bayes,” International Journal of Enhanced Research In Science Technology & Engineering, vol. 2, no. 3, pp. 1–5, 2013.

[16] R. Das, I. Turkoglu, and A. Sengur, “Effective diagnosis of heart disease through neural networks ensembles,” Expert systems with applications, vol. 36, no. 4, pp. 7675–7680, 2009.

[17] Chen et al., “HDPS: Heart disease prediction system,” in Computting in Cardiology, Hangzhou, China: IEEE, 2011, pp. 557–560.

[18] V. Sabarinathan and V. Sugumaran, “Diagnosis of heart disease using decision tree,” International Journal of Research in Computer Applications & Information Technology, vol. 2, no. 6, pp. 74–79, 2014.

[19] J. Patel et al., “Heart disease prediction using machine learning and data mining technique,” Heart Disease, vol. 7, no. 1, pp. 129–137, 2015

[20] W. Wiharto, H. Kusnanto, and H. Herianto, “Performance analysis of multiclass support vector machine classification for diagnosis of coronary heart diseases,” International Journal on Computational Science & Applications, vol. 5, no. 5, pp. 27–37, 2015.

[21] N. Khateeb and M. Usman, “Efficient heart disease prediction system using k-nearest neighbor classification technique,” in Proceedings of the International Conference on Big Data and Internet of Thing (BDIOT), New York, NY, USA: ACM, 2017, pp. 21–26.

[22] S. Pouriyeh et al., “A comprehensive investigation and comparison of machine learning techniques in the domain of heart disease,” in Proceedings of IEEE Symposium on Computers and Communications (ISCC). Heraklion, Greece: IEEE, July 2017, pp. 204–207.

[23] S. Amin, K. Agarwal, and R. Beg, “Genetic neural network based data mining in prediction of heart disease using risk factors,” in IEEE Conference on Information Communication Technologies. Thuckalay, Tamil Nadu, India, April 2013, pp. 1227–1231.

[24] B. Venkatalakshmi and M. Shivsankar, “Heart disease diagnosis using predictive data mining,” International Journal of Innovative Research in Science, Engineering and Technology, vol. 3, no. 3, pp. 1873–1877, 2014.

[25] S. Palaniappan and R. Awang, “Intelligent heart disease prediction system using data mining techniques,” in IEEE/ACS International Conference

on Computer Systems and Applications. Doha, Qatar, March 2008, pp. 108–115.
[26] S. Ghumbre, C. Patil, and A. Ghatol, "Heart disease diagnosis using support vector machine," in International conference on computer science and information technology. Pattaya, Thailand: Planetary Scientific Research Centre, 2011, pp. 84–88
[27] Reddy, K.V.V.; Elamvazuthi, I.; Aziz, A.A.; Paramasivam, S.; Chua, H.N.; Pranavanand, S. Heart Disease Risk Prediction Using Machine Learning Classifiers with Attribute Evaluators. Appl. Sci. 2021, 11, 8352
[28] Perumal, R. Early prediction of coronary heart disease from cleveland dataset using machine learning techniques. Int. J. Adv. Sci. Technol. 2020, 29, 4225–4234
[29] Amin, M.S.; Chiam, Y.K.; Varathan, K.D. Identification of significant features and data mining techniques in predicting heart disease. Telemat. Inform. 2019, 36, 82–93.
[30] Mohan, S.; Thirumalai, C.; Srivastava, G. Effective heart disease prediction using hybrid machine learning techniques. IEEE Access 2019, 7, 81542–81554
[31] Dwivedi, A.K. Performance evaluation of different machine learning techniques for prediction of heart disease. Neural Comput. Appl. 2018, 29, 685–693
[32] Ashraf, M.; Ahmad, S.M.; Ganai, N.A.; Shah, R.A.; Zaman, M.; Khan, S.A.; Shah, A.A. Prediction of Cardiovascular Disease Through Cutting-Edge Deep Learning Technologies: An Empirical Study Based on TENSORFLOW, PYTORCH and KERAS. In International Conference on Innovative Computing and Communications; Springer: Berlin/Heidelberg, Germany, 2021; pp. 239–255
[33] Das, S. P., & Padhy, S. (2018). A novel hybrid model using teaching–learning-based optimization and a support vector machine for commodity futures index forecasting. International Journal of Machine Learning and Cybernetics, 9(1), 97–111. https://doi.org/10.1007/s13042-015-0359-0
[34] Kanungo, D. P., Nayak, J., Naik, B., & Behera, H. S. (2016). Hybrid Clustering using Elitist Teaching Learning-Based Optimization. International Journal of Rough Sets and Data Analysis. https://doi.org/10.4018/ijrsda.2016010101
[35] Tan, Y., & Wang, J. (2004). A support vector machine with a hybrid kernel and minimal vapnik-chervonenkis dimension. IEEE Transactions on Knowledge and Data Engineering, 16(4), 385–395. https://doi.org/10.1109/tkde.2004.1269664
[36] Cervantes, J., García-Lamont, F., Rodríguez-Mazahua, L., & López, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing, 408, 189–215. https://doi.org/10.1016/j.neucom.2019.10.118
[37] Hosseini, S., & Zade, B. M. H. (2020). New hybrid method for attack detection using combination of evolutionary algorithms, SVM, and ANN. Computer Networks, 173, 107168. https://doi.org/10.1016/j.comnet.2020.107168
[38] Masood, F., Ahmad, J., Shah, S. a. A., Jamal, S. S., & Hussain, I. (2020). A Novel Hybrid Secure Image Encryption Based on Julia Set of Fractals and 3D Lorenz Chaotic Map. Entropy, 22(3), 274. https://doi.org/10.3390/e22030274
[39] Faisal, M., Zamzami, E. M., & Sutarman. (2020). Comparative Analysis of Inter-Centroid K-Means Performance using Euclidean Distance, Canberra Distance and Manhattan Distance. Journal of Physics, 1566(1), 012112. https://doi.org/10.1088/1742-6596/1566/1/012112
[40] Rao, R. R., Savsani, V., & Vakharia, D. P. (2011). Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems. Computer Aided Design, 43(3), 303–315. https://doi.org/10.1016/j.cad.2010.12.015