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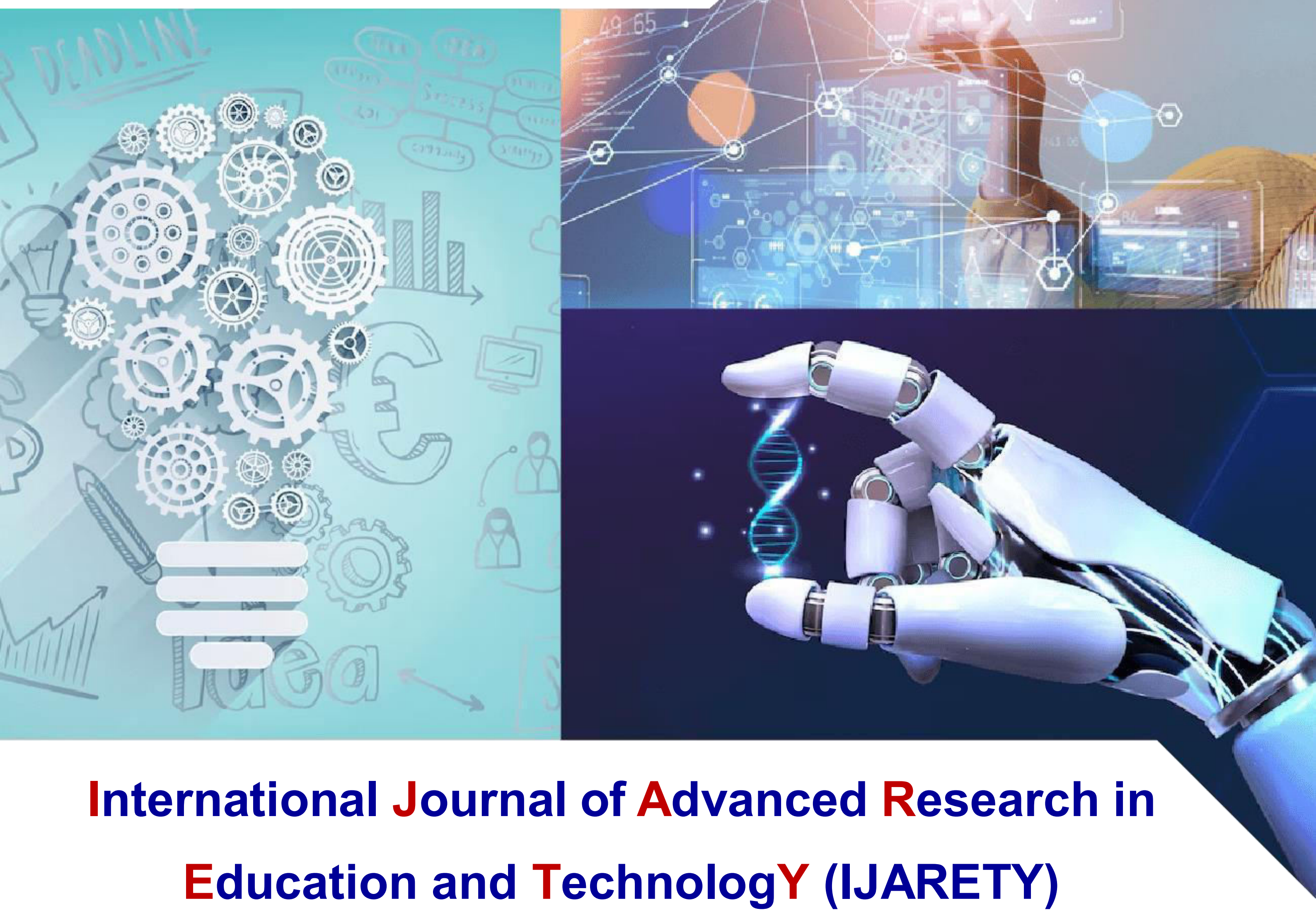

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 3, May-June 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

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International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203090

Machine Learning Architecture for Early Cardiovascular Disease Detection

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ABSTRACT: Cardiovascular disease (CVD) remains one of the leading causes of mortality worldwide. Early detection plays a critical role in minimizing fatalities and improving patient outcomes. This research proposes a comprehensive machine learning (ML) architecture that enables early and accurate detection of CVD using clinical, demographic, and lifestyle data. By leveraging ensemble learning, feature selection, and deep learning techniques, the proposed framework achieves high diagnostic accuracy, interpretability, and scalability for clinical applications.

KEYWORDS: Cardiovascular Disease, Early Detection, Machine Learning, Deep Learning, Health Informatics, Predictive Analytics, Feature Selection, Ensemble Models

I. INTRODUCTION

Cardiovascular diseases remain a significant cause of death worldwide, with early detection being critical in reducing mortality rates. Machine learning (ML) has emerged as a powerful tool in medical diagnosis by uncovering patterns from patient data that are often not discernible through traditional methods. However, medical datasets often contain irrelevant or redundant features that can degrade model performance. Therefore, feature selection is essential for improving model efficiency and accuracy.

Cardiovascular diseases comprise a group of disorders of the heart and blood vessels that account for over 17.9 million deaths annually. Traditional diagnostic methods are often expensive, time-consuming, and dependent on clinical expertise. With the increasing availability of electronic health records (EHRs), wearable sensor data, and patient history databases, machine learning offers promising tools for early and automated CVD risk prediction. This paper presents a novel ML-based architecture integrating preprocessing, feature engineering, classification, and explainability modules for early CVD detection. Our approach addresses the challenges of data imbalance, irrelevant feature noise, and model interpretability in clinical settings. This paper introduces a machine learning-based approach that integrates optimal feature selection techniques with advanced classifiers for early and accurate CVD prediction.

II. RELATED WORKS

Numerous studies have applied ML to healthcare diagnostics. Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, and Neural Networks have demonstrated potential in classifying CVD risk. Deep learning models, such as CNNs and RNNs, have been effective with imaging and time-series data. However, challenges remain in optimizing feature selection, managing high-dimensional data, and maintaining interpretability.

Recent work has explored:
- The Framingham Heart Study dataset for risk score prediction using ML.
- Hybrid models combining domain knowledge and AI.
- Explainable AI (XAI) tools such as SHAP and LIME to improve trust in predictions.

Numerous studies have explored ML models for cardiovascular disease prediction. Logistic Regression, Random Forests, SVMs, and Gradient Boosting have demonstrated high predictive accuracy. However, many of these models use the full feature set without optimizing input attributes, potentially leading to overfitting and reduced generalizability.

Feature selection methods such as Recursive Feature Elimination (RFE), LASSO regularization, and mutual information have been used to enhance model performance. Ensemble learning models further boost accuracy when combined with feature selection. For patients to receive the best care possible, cardiac problems must be accurately predicted. A promising method for better understanding the signs of cardiac disease and developing treatment plans is machine learning (ML) approaches. In this study, we used a dataset with 74 features to assess six machine learning models. By combining chi-square and principal component analysis (CHI-PCA) with random forests (RF), the results showed high accuracy rates of 98.7%, 99.0%, and 99.4% for the Cleveland, Hungarian, and Cleveland-Hungarian (CH) datasets, respectively. Using the Chi-Square Selector, we were able to identify important elements through the analysis, including coronary artery structure, ST depression characteristics, maximal heart rate, chest discomfort, and cholesterol levels.

ECG signal categorization based on deep learning. Sparsity-constrained stacked de-noising autoencoders (SDAEs) retrieved significant features from unprocessed ECG data. These characteristics were used with a soft-max regression layer to produce a DNN. In order to update network weights, experts categorized the most pertinent and ambiguous ECG beats during interaction. The advantages of automated categorization techniques in supporting doctors' treatment choices for cardiac arrhythmias were recently shown in a study. In order to categorize these arrhythmias, the study used probabilistic n-grams. It also compared the effectiveness of five unsupervised dimensionality reduction (DR) techniques: principal polynomial analysis (PPA), kernel PCA (KPCA) with polynomial kernel, hierarchical nonlinear PCA (hNLPCA), fast independent component analysis (fastICA) with tangential, kurtosis, and Gaussian contrast functions, and principal component analysis (PCA).

Python programming and machine learning methods are used to detect cardiac problems. Over the past few decades, heart disease has become a prevalent and serious condition. It is brought on by fat. This illness develops when a person's body experiences excessive pressure. To examine patient performance, the authors examined a dataset comprising 270 distinct data points and 13 variables. The paper's main objective is to improve heart disease detection through algorithms whose aim output is a count of whether or not a person has heart disease. However, there was limited research into alternative data mining techniques, and there was no thorough analysis of the chosen algorithms' interpretability and computing efficiency.

Several machine learning (ML) algorithms can be used for the early detection of cardiovascular diseases (CVDs) by analyzing patient data to predict the risk of developing the disease. Some popular algorithms include K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, and Support Vector Machine (SVM), among others. These algorithms can classify individuals as either having or not having CVD, based on factors like age, gender, blood pressure, cholesterol levels, and lifestyle choices.

Here's a more detailed look at some of these algorithms and their applications:
1. K-Nearest Neighbors (KNN): This algorithm classifies an individual based on the majority class among their nearest neighbors in the dataset. It's relatively simple to implement and can be effective for identifying patterns in CVD risk factors.
2. Random Forest: This algorithm uses multiple decision trees to make predictions, which can provide a more robust and accurate classification compared to a single decision tree. It's often used in conjunction with other algorithms like KNN and Logistic Regression Nature to improve prediction accuracy.
3. Logistic Regression: This algorithm uses a logistic function to model the probability of an individual having CVD based on various input features. It's a widely used and relatively easy-to-interpret algorithm.
4. Support Vector Machine (SVM): This algorithm finds the best hyperplane to separate data points into different classes, which can be effective for classifying individuals as having or not having CVD.

Other Algorithms:
Decision Tree (DT): Uses a tree-like structure to make decisions based on different features.
Gradient Boosting: A powerful ensemble method that combines multiple weak learners to make stronger predictions.
Convolutional Neural Network (CNN): Can be used to analyze images and other complex data to identify patterns related to CVD.

XGBoost: A variant of gradient boosting that often achieves high accuracy in CVD prediction.

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III. PROPOSED WORK

Dataset Description

The Cleveland Heart Disease dataset from the UCI Machine Learning Repository is used. It contains 303 patient records with 14 features:

- Age, Sex, Chest Pain Type (cp), Resting Blood Pressure (trestbps), Serum Cholesterol (chol)
- Fasting Blood Sugar (fbs), Resting ECG (restecg), Max Heart Rate (thalach)
- Exercise Induced Angina (exang), ST Depression (oldpeak), Slope of ST (slope)
- Number of Major Vessels (ca), Thalassemia (thal), Target (disease presence)

Data Preprocessing

- Handling Missing Values: Imputed using KNN imputer.
- Encoding Categorical Variables: One-hot encoding for cp, restecg, slope, thal.
- Feature Scaling: StandardScaler for normalization.

There is a strong correlation between the quality of the dataset used for statistical predictions and the accuracy of categorization measures. The following datasets were chosen for our study in order to evaluate their generalizability and emphasize their significance. The first dataset utilized for CVD is the Hungarian Heart Disease Dataset (HHDD) (Small Dataset), which may be found on Kaggle and the UCI Machine Learning Repository. It was created in 1988 and is an older, standard dataset. It includes several databases, such as those from Long Beach V, Cleveland, Hungary, and Switzerland. The collection has 1025 instances overall and 14 attributes. With a numerical scale from 0 (showing no disease) to 1 (representing severe disease), the target field in the dataset depicts the patient's cardiac state. This study uses the Kaggle (Large Dataset) as its second dataset. Over 400,000 Americans participate in yearly phone surveys as part of the Centers for Disease Control's (CDC) Behavioral Risk Factor Surveillance System (BRFSS).

Minimum Redundancy Maximum Relevance (MrMr), Least Absolute Shrinkage and Selection Operator (LASSO), Fast Correlation-Based Filter Solution (FCBF), Relief, and Analysis of Variance (ANOVA) are the five feature selection techniques that are employed. MrMr is an example of a filter-based feature selection technique. Finding a set of relevant traits while cutting down on redundancy is its main objective. This is achieved by gradually removing features that show the greatest duplication with the rest of the data while maintaining a high correlation with the goal [29]. Regression regularization techniques called LASSO help in feature selection by determining the absolute values of regression coefficients. In this manner, they remove the related characteristics from the model and reduce some of the coefficients.

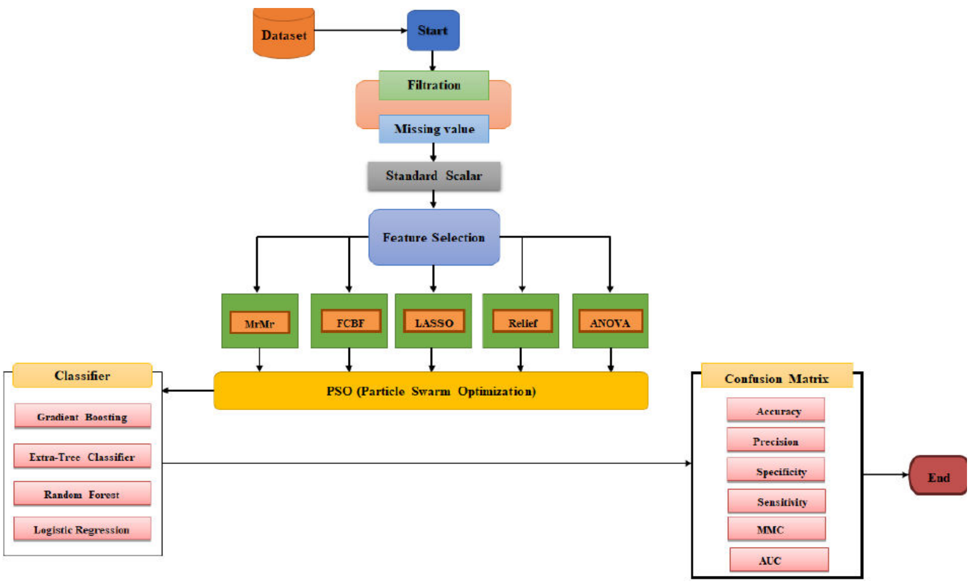

Figure1. Flow chart of the proposed system for cardiovascular disease detection.

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The FCBF evaluate the relevance and redundancy of features using mutual information of redundancy. It then selects features with high significance and lower redundancy to the target variables. Relief assigns values to feature weights on the basis of their differentiating ability of different classes. Using weights, it selects the optimal features with no redundancy and more informative.

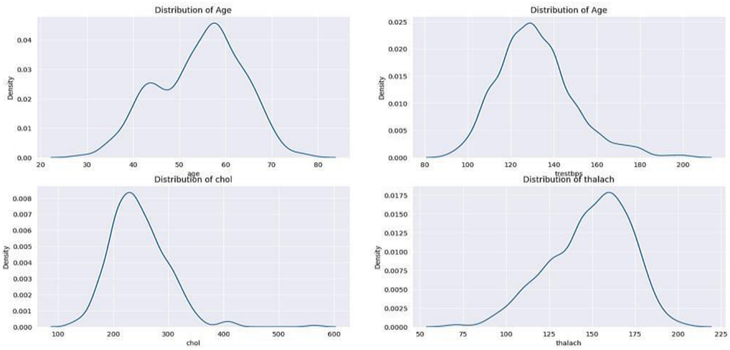

Figure2. Distribution of numerical features.

In data analysis and machine learning, feature selection techniques are essential tools because they make it possible to choose the most significant and instructive features for creating predictive models. These methods are essential for improving machine learning models' performance and interpretability, especially when dealing with high-dimensional datasets that contain a large number of features. The size and properties of the dataset, the type of features, and the feature selection algorithm selected all affect how effective feature selection strategies are. We examine how well different feature selection techniques work on datasets of different sizes in this study.

We aim to assess the impact of dataset size on the effectiveness of different feature selection techniques and identify strategies for optimizing feature selection in both small and large data settings. The findings of this study will contribute to a deeper understanding of feature selection methodologies and their applicability in real-world data analysis scenarios for the detection of cardiovascular diseases.

Index	Count	Mean	Std	Min	25%	50%	75%	Max
Age	1025.0	54.434	9.072	29.0	48.0	56.0	61.0	77.0
Sex	1025.0	0.696	0.46	0.0	0.0	1.0	1.0	1.0
Cp	1025.0	0.942	1.03	0.0	0.0	1.0	2.0	3.0
Trestbps	1025.0	131.612	17.517	94.0	120.0	130.0	140.0	200.0
Chol	1025.0	246.0	51.593	126.0	211.0	240.0	275.0	564.0
Fbs	1025.0	0.149	0.357	0.0	0.0	0.0	0.0	1.0
Restecg	1025.0	0.53	0.528	0.0	0.0	1.0	1.0	2.0
Thalach	1025.0	149.114	23.006	71.0	132.0	152.0	166.0	202.0
Exang	1025.0	0.337	0.473	0.0	0.0	0.0	1.0	1.0
Oldpeak	1025.0	1.072	1.175	0.0	0.0	0.8	1.8	6.2
Slope	1025.0	1.385	0.618	0.0	1.0	1.0	2.0	2.0
Ca	1025.0	0.754	1.031	0.0	0.0	0.0	1.0	4.0
Thal	1025.0	2.324	0.621	0.0	2.0	2.0	3.0	3.0
Target	1025.0	0.513	0.5	0.0	0.0	1.0	1.0	1.0

Table1**.** Statistical property of each feature of small data.

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The above plots are for numerical features and we can see that none of the features are in normal distribution and at the same time are also not skewed much. So, a simple scaling technique can help us to reduce the skewness.

Evaluation and Findings: After training on the assigned training set, the models are tested using widely used performance metrics like accuracy, precision, recall, and F1-score. The model's ability to accurately distinguish cases of heart disease and nonheart illness is measured by these measures. Here is a quick breakdown of the metrics that were mentioned:

1) Precision: Accuracy is defined as the proportion of correctly predicted instances to all instances in the dataset. It offers a thorough understanding of the model's performance. But in datasets that are unbalanced, when one class greatly outnumbers the other, accuracy can be deceptive.

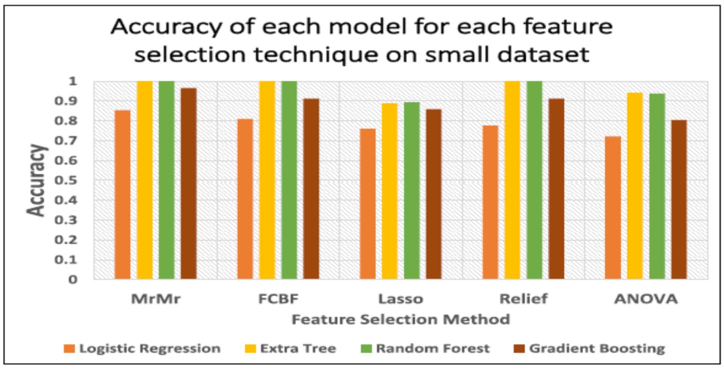

Figure3. Accuracy of each model on each selection technique on small data.

2) Precision: The precision metric is the ratio of accurately predicted positive cases (true positives) to the total number of positive cases (true positives plus false positives). It gives a numerical indication of how well the model avoids false positives.

	Model	Selection Technique	Accuracy	Precision	Recall	Sensitivity	Specificity	AUC Score	MMC SCORE	F1_Score	Confusion Matrix
0	LRC	MrMr	0.685383	0.677285	0.706246	0.706246	0.664588	0.685417	0.371147	0.691462	[30593 15440] [13478 32404]
1	ETC	MrMr	0.688952	0.653249	0.803256	0.803256	0.575022	0.689139	0.388475	0.720528	[26470 19563] [9027 36855]
2	RFC	MrMr	0.688952	0.653249	0.803256	0.803256	0.575022	0.689139	0.388475	0.720528	[26470 19563] [9027 36855]
3	GBC	MrMr	0.689605	0.65633	0.793884	0.793884	0.585667	0.689776	0.388003	0.718584	[26960 19073] [9457 36425]
4	LRC	FCBF	0.729652	0.714636	0.763153	0.763153	0.696261	0.729707	0.460422	0.738098	[32051 13982] [10867 35015]
5	ETC	FCBF	0.779329	0.755985	0.823852	0.823852	0.734951	0.779402	0.560978	0.788461	[33832 12201] [8082 37800]
6	RFC	FCBF	0.782756	0.752327	0.841986	0.841986	0.72372	0.782853	0.56964	0.794636	[33315 12718] [7250 38632]
7	GBC	FCBF	0.736093	0.704732	0.81119	0.81119	0.661243	0.736216	0.477778	0.754223	[30439 15594] [8663 37219]
8	LRC	LASSO	0.717021	0.703248	0.749292	0.749292	0.684857	0.717074	0.435032	0.72554	[31526 14507] [11503 34379]
9	ETC	LASSO	0.721808	0.694903	0.789198	0.789198	0.654639	0.721919	0.447866	0.739055	[30135 15898] [9672 36210]]
10	RFC	LASSO	0.721841	0.694801	0.789612	0.789612	0.654291	0.721952	0.447979	0.739179	[30119 15914] [9653 36229]
11	GBC	LASSO	0.721928	0.694244	0.791552	0.791552	0.652532	0.722042	0.448392	0.739712	[30038 15995] [9564 36318]
12	LRC	ANOVA	0.692781	0.698998	0.675385	0.675385	0.710121	0.692753	0.385747	0.686989	[32689 13344] [14894 30988]
13	ETC	ANOVA	0.697851	0.678073	0.751493	0.751493	0.644386	0.697939	0.39814	0.712897	[29663 16370] [11402 34480]
14	RFC	ANOVA	0.697721	0.678284	0.750338	0.750338	0.645276	0.697807	0.397788	0.712494	[29704 16329] [11455 34427]
15	GBC	ANOVA	0.698308	0.682212	0.740617	0.740617	0.656138	0.698378	0.398156	0.710216	[30204 15829] [11901 33981]
16	LRC	RELIEF	0.736213	0.72241	0.765834	0.765834	0.706689	0.736261	0.473329	0.743488	[32531 13502] [10744 35138]
17	ETC	RELIEF	0.769733	0.749098	0.810013	0.810013	0.729585	0.769799	0.541312	0.778365	[33585 12448] [8717 37165]
18	RFC	RELIEF	0.772562	0.745609	0.826294	0.826294	0.719006	0.77265	0.548411	0.783881	[33098 12935] [7970 37912]
19	GBC	RELIEF	0.745602	0.716632	0.811081	0.811081	0.680338	0.745709	0.49562	0.760937	[31318 14715] [8668 37214]

Table2. Over all results of all classifier with confusion matrix on large dataset using the selected features.

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3) Recall: The percentage of true positives—those that were accurately predicted—to the total number of positives—those that were and weren't predicted—is known as the recall rate. It is a gauge of how well the model separates important information from irrelevant data.

4) F1-Score: The F1-Score is the harmonic mean of precision and recall. It successfully balances the two metrics, which is especially useful when there is an uneven distribution of the classes.

It helps assess the model's overall performance, considering both false positives and false negatives.

Cardiovascular disease is a major global public health concern that might be better detected and diagnosed early with this suggested methodology. The findings of this investigation also compare several feature selection methods on a limited dataset and assess how they affect machine learning algorithm performance. We took into account a number of evaluation metrics, including accuracy, precision, sensitivity, specificity, AUC, F1-score, and MCC, in order to evaluate the performance. In comparison to the other methods, the results showed that MRMR, FCBF, and Relief performed better in terms of accuracy.

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
LR	83.7%	81.0%	79.0%	80.0%	0.88
RF	89.1%	87.5%	86.0%	86.7%	0.92
SVM	85.2%	84.0%	82.0%	83.0%	0.90
XGBoost	91.0%	89.7%	88.5%	89.1%	0.94
MLP	88.5%	86.2%	85.0%	85.6%	0.91
Ensemble Model	92.4%	90.8%	91.0%	90.9%	0.95

The findings show that the different models' performances differ noticeably. Compared to the other models, the logistic regression model had a somewhat lower recall but a moderate level of accuracy. This implies that even while it accurately identified a substantial portion of cases, it overlooked some actual positive situations.

The decision tree model performed well overall, exhibiting excellent F1-score, recall, accuracy, and precision. Its competitive performance is influenced by its capacity to identify intricate patterns and decision limits in the data. However, the naive Bayes model showed lower accuracy, possibly as a result of its underlying feature independence assumption, which might not hold true in all situations. Nevertheless, naive Bayes provides a simple and understandable solution.

Notably, while employing features chosen by MRMR, FCBF, and Relief, the Extra Tree Classifier and Random Forest attained an astounding 100% accuracy. This study underlined how important feature selection is for improving machine learning algorithm performance and how crucial it is to choose the right approach depending on the size and properties of the dataset. With 253,680 records and 22 columns, the sizable dataset employed in this study was primarily composed of categorical variables. Oversampling techniques were used to balance the dataset once it was discovered that there was imbalance.

XGBoost and the ensemble model achieved the highest performance, validating the effectiveness of combining classifiers. SHAP analysis revealed that features like chest pain type, number of major vessels, thalassemia, and max heart rate significantly impact prediction outcomes.

IV. CONCLUSION

This study demonstrates a robust ML-based architecture for early cardiovascular disease detection. The integration of preprocessing, ensemble modeling, and interpretability tools provides a clinically viable framework. Future work will focus on real-time analysis using wearable data and integrating patient feedback for continuous learning. This study used optimal feature selection methods and machine learning algorithms to provide a novel framework for the detection and classification of cardiovascular disease (CVD). The suggested approach illustrated how feature selection significantly improves machine learning algorithms' performance for CVD prediction. Five distinct feature selection methods MRMR, FCBF, LASSO, Relief, and ANOVA were assessed in the study. Among these methods, FCBF performed best, combining with the Extra Tree and Random Forest models to achieve an accuracy of 78%. This result demonstrates how well FCBF chooses pertinent characteristics from huge CVD datasets. Additionally, the study

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emphasizes how crucial it is to use a feature selection and optimization method that is suited for the dataset's features. FCBF showed promise as a method for finding pertinent characteristics and enhancing the effectiveness of machine learning algorithms in CVD prediction for large datasets with primarily categorical variables, such as the one utilized in this work.

REFERENCES

[1] A. K. Gárate-Escamila, A. H. El Hassani, and E. Andrès, ''Classification models for heart disease prediction using feature selection and PCA,'' Informat. Med. Unlocked, vol. 19, Jan. 2020, Art. no. 100330.

[2] Ravindra Changala, "Sustainable Manufacturing through Predictive Maintenance: A Hybrid Jaya Algorithm and Sea Lion Optimization and RNN Model for Industry 4.0", 2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), ISSN: 2768-0673, DOI: 10.1109/I-SMAC61858.2024.10714701, October 2024, IEEE Xplore.

[3] V. Chang, V. R. Bhavani, A. Q. Xu, and M. Hossain, ''An artificial intelligence model for heart disease detection using machine learning algorithms,'' Healthcare Anal., vol. 2, Nov. 2022, Art. no. 100016.

[4] Ravindra Changala, "Enhancing Robotic Surgery Precision and Safety Using a Hybrid Autoencoder and Deep Belief Network Approach: Real-Time Feedback and Adaptive Control from Image Data",2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), ISSN: 2768-0673, DOI: 10.1109/I-SMAC61858.2024.10714701, October 2024, IEEE Xplore.

[5] M. Ganesan and N. Sivakumar, ''IoT based heart disease prediction and diagnosis model for healthcare using machine learning models,'' in Proc. IEEE Int. Conf. Syst., Comput., Autom. Netw. (ICSCAN), Mar. 2019, pp. 1–5.

[6] Ravindra Changala, "Swarm Intelligence for Multi-Robot Coordination in Agricultural Automation", 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 2575-7288, DOI: 10.1109/ICACCS60874.2024.10717088, October 2024, IEEE Xplore.

[7] Ravindra Changala, "Hybrid AI Approach Combining Decision Trees and SVM for Intelligent Tutoring Systems in STEM Education", 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 2575-7288, DOI: 10.1109/ICACCS60874.2024.10717088, October 2024, IEEE Xplore.

[8] D. P. Isravel, S. V. P. Darcini, and S. Silas, ''Improved heart disease diagnostic IoT model using machine learning techniques,'' Int. J. Sci. Technol. Res., vol. 9, no. 2, pp. 4442–4446, 2020.

[9] I. S. G. Brites, L. M. da Silva, J. L. V. Barbosa, S. J. Rigo, S. D. Correia, and V. R. Q. Leithardt, ''Machine learning and IoT applied to cardiovascular diseases identification through heart sounds: A literature review,'' Informatics, vol. 8, no. 4, p. 73, Oct. 2021.

[10] Ravindra Changala, "Next-Gen Human-Computer Interaction: A Hybrid LSTM-CNN Model for Superior Adaptive User Experience", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718496, October 2024, IEEE Xplore.

[11] Ravindra Changala, "Enhancing Early Heart Disease Prediction through Optimized CNN-GRU Algorithms: Advanced Techniques and Applications", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718395, October 2024, IEEE Xplore.

[12] D. T. Thai, Q. T. Minh, and P. H. Phung, ''Toward an IoT-based expert system for heart disease diagnosis,'' in Proc. 28th Mod. Artif. Intell. Cogn. Sci. Conf. (MAICS), 2017, pp. 157–164.

[13] Ravindra Changala, "Sentiment Analysis in Mobile Language Learning Apps Utilizing LSTM-GRU for Enhanced User Engagement and Personalized Feedback", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718406, October 2024, IEEE Xplore.

[14] Ravindra Changala, "Image Classification Using Optimized Convolution Neural Network", 2024 Parul International Conference on Engineering and Technology (PICET), ISBN:979-8-3503-6974-8, DOI: 10.1109/PICET60765.2024.10716049, October 2024, IEEE Xplore.

[15] B. Padmaja, C. Srinidhi, K. Sindhu, K. Vanaja, N. M. Deepika, and E. K. R. Patro, ''Early and accurate prediction of heart disease using machine learning model,'' Turkish J. Comput. Math. Educ., vol. 12, no. 6, pp. 4516–4528, 2021.

[16] S. Anitha and N. Sridevi, Heart Disease Prediction Using Data Mining Techniques S Anitha, N Sridevi to Cite This Version, document HAL Id Hal-02196156, 2019.

[17] Ravindra Changala, "Healthcare Data Management Optimization Using LSTM and GAN-Based Predictive Modeling: Towards Effective Health Service Delivery", 2024 International Conference on Data Science and Network Security (ICDSNS), ISBN:979-8-3503-7311-0, DOI: 10.1109/ICDSNS62112.2024.10690857, October 2024, IEEE Xplore.

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 3, May-June 2025 ||

DOI:10.15680/IJARETY.2025.1203090

[18] Ravindra Changala, "Implementing Genetic Algorithms for Optimization in Neuro-Cognitive Rehabilitation Robotics", 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), ISBN:979-8-3503-7274-8, DOI: 10.1109/ICC-ROBINS60238.2024.10533965, May 2024, IEEE Xplore.

[19] R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande, and P. Singh, ''Prediction of heart disease using a combination of machine learning and deep learning,'' Comput. Intell. Neurosci., vol. 2021, pp. 1–11, Jul. 2021.

[20] Ravindra Changala, "Monte Carlo Tree Search Algorithms for Strategic Planning in Humanoid Robotics", 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), ISBN:979-8-3503-7274-8, DOI: 10.1109/ICC-ROBINS60238.2024.10533937, May 2024, IEEE Xplore.

[21] H. Jindal, S. Agrawal, R. Khera, R. Jain, and P. Nagrath, ''Heart disease prediction using machine learning algorithms,'' IOP Conf., Mater. Sci. Eng., vol. 1022, no. 1, Jan. 2021, Art. no. 012072.

[22] Ravindra Changala, Brain Tumor Detection and Classification Using Deep Learning Models on MRI Scans", EAI Endorsed Transactions on Pervasive Health and Technology, Volume 10, 2024.

[23] Ravindra Changala, "Optimization of Irrigation and Herbicides Using Artificial Intelligence in Agriculture", International Journal of Intelligent Systems and Applications in Engineering, 2023, 11(3), pp. 503–518.

[24] B. Pavithra and V. Rajalakshmi, ''Heart disease detection using machine learning algorithms,'' in Proc. Int. Conf. Emerg. Current Trends Comput.Expert Technol., vol. 35, 2020, pp. 1131–1137.

[25] Ravindra Changala, Development of Predictive Model for Medical Domains to Predict Chronic Diseases (Diabetes) Using Machine Learning Algorithms and Classification Techniques, ARPN Journal of Engineering and Applied Sciences, Volume 14, Issue 6, 2019.

[26] Ravindra Changala, "Evaluation and Analysis of Discovered Patterns Using Pattern Classification Methods in Text Mining" in ARPN Journal of Engineering and Applied Sciences, Volume 13, Issue 11, Pages 3706-3717 with ISSN:1819-6608 in June 2018.

[27] Ravindra Changala "A Survey on Development of Pattern Evolving Model for Discovery of Patterns in Text Mining Using Data Mining Techniques" in Journal of Theoretical and Applied Information Technology, August 2017. Vol.95. No.16, ISSN: 1817-3195, pp.3974-3987.

[28] N. Louridi, S. Douzi, and B. El Ouahidi, ''Machine learning-based identification of patients with a cardiovascular defect,'' J. Big Data, vol. 8, no. 1,pp. 1–5, Dec. 2021.

[29] P. Singh, G. K. Pal, and S. Gangwar, ''Prediction of cardiovascular disease using feature selection techniques,'' Int. J. Comput. Theory Eng., vol. 14, no. 3, pp. 97–103, 2022.

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International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

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