Multivariate Radial Interpolation Based Ruzicka Indexive Censored Regression for Early Prediction of Cardiovascular Disease

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***Abstract* - Cardiovascular diseases(CVDs) are widespread disease affecting heart as well as blood vessels, resulting in various complications like heart attacks, strokes, and peripheral artery disease. These diseases are extremely diverse as well as lead to dissimilar kinds of difficulty to minimize quality of life as well as even decease. Early detection and effective management of risk factors play pivotal roles for preventing complications and enhancing outcomes for individuals affected with cardiovascular disease. Many machine learning techniques have designed to solve heart problems, but higher prediction accuracy level with minimal time and space complexity remained challenging issues. To enhance cardiovascular disease forecast accuracy, a novel method called Multivariate Radial Interpolation based Ruzicka indexive censored regression (MRI-RICR) is introduced. The proposed MRI-RICR method utilizes the Multivariate radial basis interpolation method to estimate missing information points depend on recognized data points. Chauvinist's criterion is employed for identifying and removing outlier data from the dataset. MRI-RICR method utilizes the Ruzicka indexive censored regression method to select relevant features. This process improves the accuracy of cardiovascular disease prediction through lesser time utilization. Experimental assessment considers cardiovascular disease prediction accuracy, precision, cardiovascular disease prediction time and space complexity. The analyzed outcomes show which MRI-RICR method attain effective performance results, containing superior cardiovascular disease prediction accuracy, precision, through reduced time utilization ,space complexity than the existing techniques.**

Keywords: cardiovascular disease prediction, data preprocessing, Multivariate radial basis interpolation method, Chauvinist's criterion, Ruzicka indexive censored regression

I. INTRODUCTION

CVDs are collection of disorders influencing heart as well as blood vessels, surrounding situation such as coronary artery disease, and so on. CVDs remain the leading cause of mortality posing significant health challenges on healthcare systems. Early identification and intervention are critical in mitigating the risk factors associated with CVDs and preventing poor outcomes. There has been a variety of ML methods to design accurate and reliable methods for cardiovascular disease prediction and risk factors analysis.

QPSO method, combined with a SVM classification method, known as QPSO-SVM, was developed in [1] to examine as well as forecast heart disease danger. However, designed model failed to perform the minimization of time and space complexity during cardiovascular disease prediction. ACVD-HBOMDL method was developed in [2], aimed to improve accuracy of automated cardiovascular disease forecast. However, it did not include outlier detection processes to enhance result of cardiovascular disease forecast.

A robust, effectual, and effective ML algorithm was presented in [3] for early prediction of CVD through the selection of key features. However, it did not develop additional precise and robust scheme for forecast as well as premature diagnosis of heart diseases. The stochastic gradient boosting method was designed in [4], aims to recognize presence and deficiency of heart disease with DTRF classifier through loss optimization.

Correlation-based Feature Subset Selection technique was introduced in [5], aimed to select the most significant factors for diagnosing heart disease. But, accuracy level of diagnosing heart disease was not improved at the required level. An ensemble-based approach was designed in [6] that utilize ML and DL methods with aim of predicting cardiovascular disease. However, the method did not effectively identify the most relevant features for predicting cardiovascular disease.

However, the outlier detection process was not included to enhance the classification performance. The main contribution of the study includes the following

- To improve cardiovascular disease prediction, MRI-RICR method is developed, incorporating data preprocessing and feature selection techniques.
- The Multivariate Radial Basis Interpolation method is utilized in the MRI-RICR method for handling missing data in the dataset. The Chauvenet's criterion is applied for removing outlier data.
- The MRI-RICR method utilizes Ruzicka indexive censored regression to select most pertinent aspect as of the database, so enhancing accuracy of cardiovascular disease prediction while minimizing time consumption.
- Finally, experimental assessment is conducted to estimate result of MRI-RICR method using various metrics and comparing it to other conventional methods.

This paper discusses recent technology and different algorithms described in section 2; the proposed methodology explains the liver tumor preprocessing approach in contrast to limited adaptive equalization detail in section 3; the analysis of liver tumor preprocessing approaches the result in section 4; and finally, this proposed study method concluded in section 5.

II. RELATED WORKS

ML, neuro-fuzzy, and statistical techniques were developed [7] for early forecast of cardiovascular diseases. However, the computational complexity analysis of the early prediction in cardiovascular diseases was found to be high. A hybrid 1D CNN was developed in [8] for CVD prediction

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using a large dataset as well as chosen aspect obtained through feature selection algorithms. However, it failed for robust as well as precise prediction of heart health situations. Precise as well as effective decision support scheme depend on a machine learning method was designed in [9] to forecast nonexistence or presence of CVD as well as its severity level. However, outlier recognition as well as removal, as well as feature selection, were not incorporated, for enhancing the detection and classification of disease severity levels.

A gradient descent optimization algorithm and CNN were developed in [10] to identify cardiovascular abnormalities. However, a larger dataset was not utilized to enhance the detection of additional cardiac abnormalities. CNN was developed [11] for cardiovascular disease prediction. However, it did not minimize computational difficulty of method with no compromising accuracy. LSTM-based DNN was developed in [12] for early prediction of cardiovascular diseases (CVDs) using regression analysis, aspiring to improve accuracy level of disease forecast.

Multi-class classifier was developed in [13] for forecast of various kinds of cardiovascular diseases. However, it exhibits higher time complexity in context of cardiovascular disease forecast. K-Nearest Neighbor Algorithm, designed in [14], aimed to improve diagnostic accuracy of ischemic cardiovascular disease. However, it did not succeed in developing efficient techniques for properly monitoring critical heart patients. An automated Cardiovascular Disease Diagnosis was developed with the Honey Badger Optimization through a Modified DL approach [15]. A Hybrid Deep Neural Networks (HDNNs) was developed in [16] for robust heart disease prediction. However, a novel approach was not applied to strengthen and enhance disease prediction. A logistic regression (LR) technique was employed in [17] to categorize cardiac disease depend on data preprocessing as well as feature selection. However, time complexity of the heart disease classification remained unaddressed.

An effectual ensemble technique depend on RF method was developed in [18] to improve accuracy of cardiovascular disease forecast by integrating multiple feature selection techniques. A predictive models depend on ML were designed [19] for assessing risk of cardiovascular disease (CVD). A hybrid ECG-based deep network was developed in [20] for early classification of cardiovascular disease in hypertension patients. However, it consumed a longer time for cardiovascular disease prediction. DCNN was designed [21] for early recognition of heart disease. However, the existing methods does not improve accuracy of heart disease risk forecast methods or in developing additional effectual strategies for protecting and handling heart disease. Table 1 lists the various studies related to present study.

Table 1 : Existing Studies in the literature

Ref No.	Method	Objective	Limitation
[7]	ML, neuro-fuzzy, and statistical techniques	Early forecast of cardiovascular diseases	High computational complexity
[8]	Hybrid 1D CNN with feature selection	CVD prediction using large dataset and selected features	Lacked robust and precise prediction
[9]	ML-based decision support scheme	Forecast presence/absence and severity level of CVD	No outlier recognition/removal and feature selection
[10]	Gradient descent optimization and CNN	Identification of cardiovascular abnormalities	Did not use larger datasets for detecting additional abnormalities
[11]	CNN	Cardiovascular disease prediction	Did not minimize computational difficulty without compromising accuracy
[12]	LSTM-based DNN with regression analysis	Early prediction of CVDs aiming to improve accuracy	—
[13]	Multi-class classifier	Forecast of various kinds of cardiovascular diseases	High time complexity
[14]	K-Nearest Neighbor Algorithm	Improve diagnostic accuracy of ischemic cardiovascular disease	Inefficient for monitoring critical heart patients
[15]	Modified DL with Honey Badger Optimization	Automated CVD diagnosis	—
[16]	Hybrid Deep Neural Networks (HDNNs)	Robust heart disease prediction	Did not apply novel approach to strengthen prediction
[17]	Logistic Regression with preprocessing and feature selection	Categorize cardiac disease	Time complexity remained unaddressed
[18]	Ensemble technique based on Random Forest (RF)	Improve accuracy of CVD forecast by integrating multiple feature selection techniques	—
[19]	Predictive ML models	Assess risk of cardiovascular disease	—
[20]	Hybrid	Early	Longer

	ECG-based deep network	classification of CVD in hypertension patients	prediction time
[21]	Deep Convolutional Neural Network (DCNN)	Early recognition of heart disease	Did not improve accuracy or develop additional effective strategies for managing heart disease

There are many ML, DL and hybrid approaches developed to predict cardiovascular disease and there are some critical issues that have not been addressed. The vast number of previous studies cannot be used by practitioners because of computational complexity and time complexity, meaning they cannot be performed in real time. There are also no solid procedures for feature selection or outlier removal, which misleads the predictive accuracy and generalizability of the results, as well as a lack of viable approaches to support scalability. Further, there has not been a clear integrated framework that supports accurate and efficient early diagnosis and simultaneously deals with the wide breadth of cardiovascular diseases.

III. PROPOSED METHODOLOGY

CVD is important health concern including variety of situation which influences heart as well as blood vessels. Predicting risk of developing CVD is essential for preventive healthcare strategies and early interventions. Various predictive models and algorithms have designed to evaluate individual's danger of rising CVD depend on age, gender, and so on. These predictive methods healthcare professionals recognize high-risk individuals with minimal time and complexity remained a challenging issues. To meet these gaps, in this work a method called, MRI-RICR method for CVD prediction is designed.

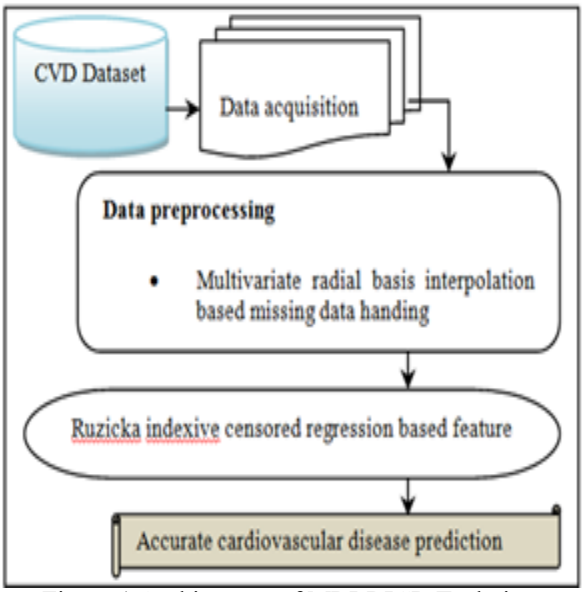

Figure 1 Architecture of MRI-RICR Techniques

Figure 1 shows the demonstrate architecture diagram of MRI-RICR technique for accurate prediction of cardiovascular disease. The accurate detection method involves three fundamental steps namely data acquisition, data preprocessing, and feature selection.

A. Data acquisition

Data acquisition is the fundamental step in the preprocessing technique. It is the process of collecting the numerous patient data from the cardiovascular disease database taken as of https://www.kaggle.com/sulianova/cardiovascular-disease-data set. By following these steps, effectively acquire high-quality data for rising as well as authenticating prognostic methods for cardiovascular disease risk assessment. Major aim of this database is to find presence and nonexistence of cardiovascular disease. The dataset consists of 13 attributes and 70000 instances.

B. Data preprocessing

The next fundamental step of the MRI-RICR method is a data preprocessing for cardiovascular disease (CVD) risk assessment. It include cleaning, transforming, organizing acquired information to organize it for CVD risk assessment investigation. Major objective of data preprocessing is to minimize time and space complexity of CVD risk prediction. The data preprocessing of MRI-RICR method includes two major processes namely missing data handling ad outlier detection. These two processes of data preprocessing is elaborated in following subsections.

Multivariate radial basis interpolation based missing data handing: Missing data refers to the absence of values in a dataset. It occurs when no data value is stored for a variable in a particular observation. Handling missing data is important in data analysis since it leads to inaccurate disease prediction if not addressed properly. There are several methods to contract through missing information. Proposed MRI-RICR method utilizes the Multivariate radial basis interpolation method for handling the missing data. The interpolation-based methods offer a balance between data maintenance, flexibility, and ease of implementation for handling missing data. Raw input dataset 'Ds' is formulated in form of matrix as below.

$$A = \begin{bmatrix} F_1 & F_2 & \dots & F_n \\ DP_{11} & DP_{12} & \dots & DP_{1n} \\ DP_{21} & DP_{22} & \dots & DP_{2n} \\ \vdots & \vdots & \dots & \vdots \\ DP_{m1} & DP_{m2} & \dots & DP_{mn} \end{bmatrix}$$

From the above input matrix *'A'* formulation where 'n' denotes a column represents the features $F_1, F_2, \dots F_n$ and the overall sample instances or patient data 'DP_{11}' presented in the 'm' row respectively.

From the input matrix *'A'* where 'n 'denotes columns representing features and *'m'* denotes rows representing overall sample instances or patient data 'DP'. Multivariate radial basis interpolation method is employed for handling the missing data. The interpolation-based methods offer a balance between data maintenance, flexibility, and ease of implementation for handling missing data. Multivariate having or involving a number of already known data points for handling missing data. Interpolation is the process of finding the unknown data values based on the known data values. First, a weighted mean concept is applied to identify the missing value in the respective feature. Weighted mean is expressed as follows,

$$DP_m = WM = \frac{\sum_{i=1}^{m} DP_i * w_i}{\sum_{i=1}^{m} w_i} \quad (1)$$

Where, WM denotes a weighted mean for finding the missing value, DP_i denotes an known data points, ω_i denotes a weight assigned to data point 'DP_i ', DP_m denotes a missing data. Thus, the multivariate radial basis interpolation offers a method to assess whether the estimation of missing values is appropriate or not.

$$\varphi = \exp(-\epsilon Q^2) \quad (2)$$

$$Q = |DP_m - DP_{nm}| \quad (3)$$

Where, φ denotes a radial basis interpolation, ε denotes a parameter used for avoiding overfitting. If ε is too small, the interpolation may capture noise in the data. Conversely, if ε is too large, the interpolation may over smooth the data. From (4),DP_m denotes a missing data, DP_{nm} denotes a non-missing data available in the dataset. An interpolated value of $\varphi = 1$ denotes determined missing value is accurate based on the available data in the dataset. Like this, every missing data are managed based on available data points in the dataset.

Ruzicka indexive censored regression based feature selection Feature selection is performed in MRI-RICR method. Feature selection, also called attribute selection, helps to select most pertinent aspects for accurate cardiovascular disease forecast. Main objective is to make predicting cardiovascular disease faster through the relevant features. The MRI-RICR method uses the Ruzicka indexive censored regression method to choose pertinent aspect as of database. It is ML method employed for measuring association among the aspects in which dependent variable i.e. features censored above or below a certain threshold. The Ruzicka index is a similarity function used for measuring the relationship between the features. The features with high similarity are selected for accurate disease prediction. Other less similarity features are removed from the dataset. This process improves the accuracy of cardiovascular disease prediction with minimal time consumption.

Figure 2 illustrates flow process of the Ruzicka indexive censored regression for accurate cardiovascular disease prediction. Let us consider the preprocessed cardiovascular disease dataset as input for feature selection process. First, number of features $F_1, F_2, \ldots F_n$ are collected as of given database.

The features are given as input to the censored regression. Censored regression is a statistical analysis when the exact value of an output variable is observed, and other values are removed due to specific constraints, referred to as censoring points. A censoring point denotes a specific value or threshold acting as a boundary, beyond which input are censored. This regression process involves two types of censoring. Left-censoring arises as the observed value of a Ruzicka index output is known to be less than a certain threshold, while right-censoring occurs when the Ruzicka index output is known to be above a certain threshold. The threshold defines lower and higher values of the Ruzicka index coefficient.

The mathematical formula for calculating the Ruzicka index between the features is shown below

$$RC = \frac{[F_i \cap F_j]}{\sum F_i + \sum F_j - [[F_i \cap F_j]} \quad (4)$$

Where, 'RC' denotes a Ruzicka similarity coefficient, F_i and F_j denotes the features, $F_i \cap F_j$ denotes a mutual dependence between the two features. The coefficient (RC) provides the output ranges between 0 and 1. Then the Left-censoring as well as right-censoring are two types of censoring events that occur in statistical analysis, particularly in censored regression

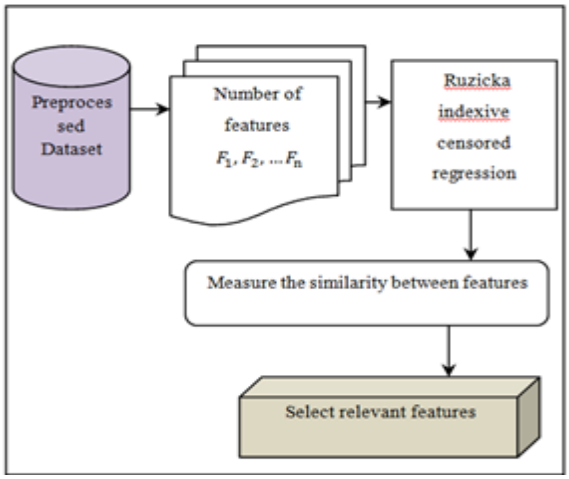

Figure 2 Workflow-Ruzicka indexive censored regression based feature selection

.Censored regression is a class of models in which the Ruzicka similarity coefficient is censored above or below a certain threshold.

$$A = \begin{cases} RC > T \; ; relavant \; features \\ RC < T \; ; irrelavant \; features \end{cases} \quad (5)$$

Where, Z indicates a censored regression output, T denotes a threshold, RC denotes a Ruzicka similarity coefficient. If the coefficient value is greater than the threshold i.e. right censoring, the relevant aspect is selected. If similarity value is less than threshold i.e. left censoring, the irrelevant feature and it is censored i.e. removed. In this manner, the Ruzicka indexive censored regression identifies relevant features. This relevant feature is used for accurate cardiovascular disease prediction.

IV. RESULTS AND DISCUSSION

Performance of the MRI-RICR method and QPSO-SVM [1] and ACVD-HBOMDL [2] are estimated through different parameters with different number of patient data.

Cardiovascular disease prediction accuracy: It refers to ratio of accurately forecasting presence or absence of cardiovascular disease from total number of patient information. Therefore, accuracy is computed below:

$$CDPA = \frac{TP+TN}{TP+TN+FN+FP} * 100 \quad (6)$$

Where, $CDPA$ indicates an cardiovascular disease prediction accuracy, TP represents true positive indicates correctly identifying cardiovascular disease presence or absence, TN indicates true negative denotes a properly identifying cardiovascular disease , FP represents the false positive represents incorrectly identifying cardiovascular disease presence or absence, FN represents the false negative indicates incorrectly predicts a absence of cardiovascular disease. It is calculated in percentage (%).

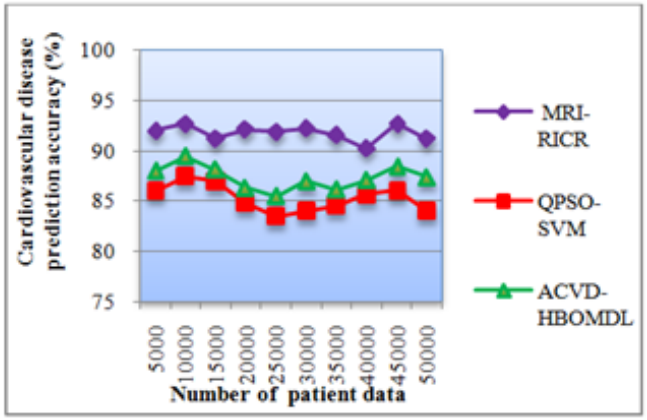

Figure 3: Performance Analysis of CDPA

Figure 3 depicts performance study of $CDPA$ using MRI-RICR, QPSO-SVM [1], and ACVD-HBOMDL [2]. Among the three techniques, result of the MRI-RICR method is notably improved compared to conventional methods. For instance, considering 5000 patient data for accuracy calculation, the MRI-RICR method attained accuracy of 92%. Furthermore, detection accuracy of conventional [1] and [2] was 86% and 88%. Ten different results were observed for each method with varying numbers of patient data. The observed results of the MRI-RICR method are compared with conventional methods. Overall comparative analysis denotes which detection accuracy of the MRI-RICR method improved considerably by 8% and 5% than the [1] , [2] respectively.

This improvement is achieved owing to relevance of the Ruzicka indexive censored regression to enhance accurate cardiovascular disease prediction. For each feature in the given dataset, Ruzicka similarity is measured. The censored regression function analyzes the similarity coefficient and distinguishes relevant and irrelevant features by setting a threshold. The relevant features are used for cardiovascular disease forecast, thus improving accuracy.

Precision: It is defined as ratio of detecting cardiovascular disease presence or absence. It is expressed as,

$$PN = \frac{TP}{TP+FP} \tag{7}$$

where, PNdenotes precision, TP indicates the true positive, FP denotes false positive. Table 1 lists the precision values for different methods.

Table 1 Precision

Number of patient data	PN		
	MRI-RICR	QPSO-SVM	ACVD-HBOMDL
5000	0.927	0.884	0.898
10000	0.923	0.878	0.902
15000	0.918	0.865	0.895
20000	0.932	0.862	0.884
25000	0.924	0.874	0.895
30000	0.917	0.865	0.887
35000	0.928	0.874	0.891
40000	0.932	0.863	0.895
45000	0.927	0.865	0.882
50000	0.918	0.852	0.875

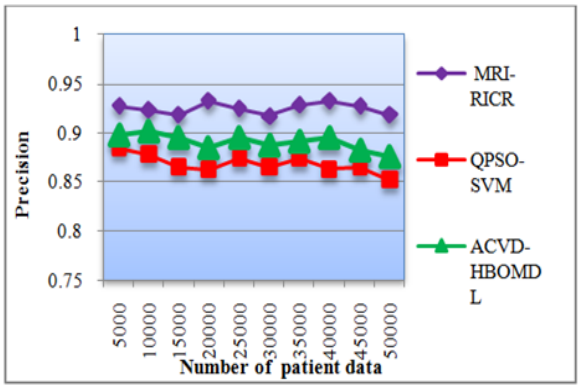

Figure 4 Performance Analysis of Precision

In Figure 4, performance results of precision are depicted versus number of patient data. Three methods, namely MRI-RICR, QPSO-SVM [1], and ACVD-HBOMDL [2], are utilized to evaluate precision. Results demonstrate that the MRI-RICR method achieves higher precision compared to two conventional methods. The examined outcomes of MRI-RICR method are compared to conventional methods. Overall comparison reveals that the precision performance in accurately detecting cardiovascular disease prediction is enhanced by 7% compared to [1] and 4% compared to [2] when applying the MRI-RICR method. To achieve this improved performance, the MRI-RICR method utilizes Ruzicka indexive censored regression for selecting more relevant features, thereby enhancing detection through improved TP and minimizing FP outcomes during cardiovascular disease prediction.

Cardiovascular disease prediction time: It is calculated as amount of time utilized through method for predicting cardiovascular disease presence or absence. It is computed as below,

$$CDPT = \sum_{i=1}^{m} DP_i * T(CDP) \tag{8}$$

where, $CDPT$ denotes a cardiovascular disease prediction time depend on patient data 'DP_i' and actual time utilized in cardiovascular disease prediction indicated by '$T(CDP)$. It is calculated in milliseconds (ms). Table 2 provides the lists of CDPT values.

Table 2 CDPT

Number of patient data	$CDPT$ (ms)		
	MRI-RICR	QPSO-SVM	ACVD-HBOMDL
5000	26.5	30	28
10000	30.2	35.7	32.4
15000	32.5	40.5	36.7
20000	36.4	42.6	40.2
25000	40.7	45.7	43.5
30000	43.8	48.9	46.9
35000	46.7	52.5	50.1
40000	50.5	55.2	53.6
45000	52.7	58.5	55.7
50000	55.9	60.7	57.6

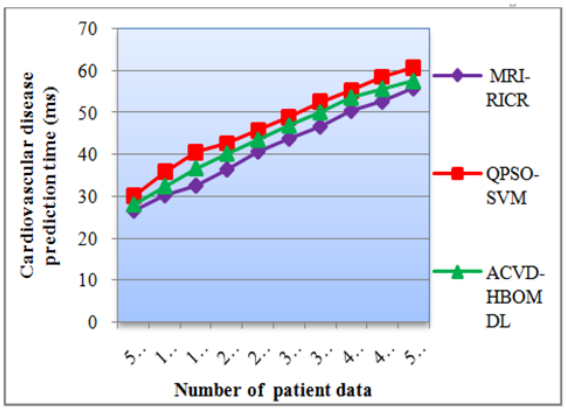

Figure 5 Performance Analysis of the proposed method - CDPT

Figure 5 depicts performance study of $CDPT$ with MRI-RICR, QPSO-SVM [1], and ACVD-HBOMDL [2]. The performance of $CDPT$ for every three methods enhances through number of patient data. Specifically, the cardiovascular disease prediction time for the MRI-RICR method is considerably minimized compared to conventional [1],[2]. Let's consider initial iteration through 5000 patient data, wherever $CDPT$ for MRI-RICR method was found to be $26.5ms$. Likewise, time consumption for [1] and [2] was $30\,ms$ and $28\,ms$. Overall outcomes attained as of MRI-RICR method are compared to results of conventional methods. Comparison results indicate which performance of cardiovascular disease prediction time using the MRI-RICR method is reduced by 12% and 7% than the [1], [2]. This reduction is owing to MRI-RICR method performing data preprocessing as well as relevant feature selection. In data preprocessing step, missing data are determined by applying Multivariate Radial Basis Interpolation-based missing data handling. The Chauvinist's criterion is employed for outlier data removal. Followed by, Ruzicka indexive censored regression is employed for accurate feature selection to enhance result of cardiovascular disease forecast. This process also minimizes the time consumption of cardiovascular disease prediction

Space complexity: It is calculated as amount of memory space utilized through method for predicting cardiovascular disease presence or absence. It is computed as below,

$$SC = \sum_{i=1}^{m} DP_i * Mem(CVD) \quad (9)$$

Where, SC denotes a space complexity depend on the patient data 'DP_i' and memory space utilized in predicting cardiovascular disease presence or absence denoted by '$Mem(CVD)$'. It is calculated in Kilobytes (KB and is shown in table 3.

Table 3 Space Complexity

Number of patient data	Space Complexity (KB)		
	MRI-RICR	QPSO-SVM	ACVD-HBOMDL
5000	165	210	190
10000	275	442	365
15000	365	502	425
20000	412	589	523
25000	528	678	625
30000	633	789	712
35000	745	925	856
40000	785	1032	912
45000	823	1152	978
50000	914	1245	1128

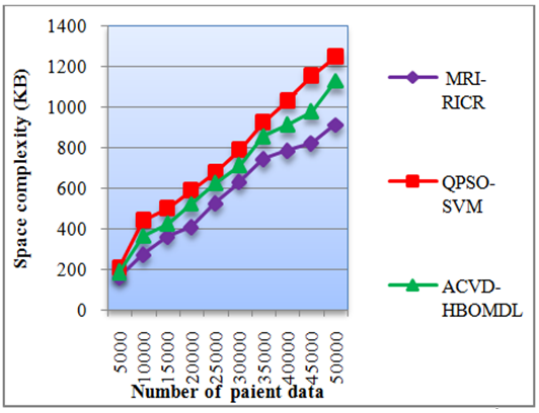

Figure 6 Performance Analysis of Space Complexity

Figure 6 depicts performance results of SC versus the number of patient data collected from dataset. As the number of patient data increases, the space complexity of every three techniques gradually enhances. Particularly, space complexity for the MRI-RICR method significantly decreases compared to [1] and [2]. Considering the results from the first iteration with 5000 patient data, the space complexity for the MRI-RICR method was 165 KB, while for [1] and [2], it was 210 KB and 190 KB, respectively. Consequently, entire outcomes of MRI-RICR method are compared to conventional techniques. Average of ten outcomes shows which result of SC is minimized by 26% and 16% than the existing QPSO-SVM [1] , ACVD-HBOMDL [2]. This reduction is achieved by minimizing the dimensionality of the dataset through the feature selection process. This method selects more relevant features while removing others from the dataset, thereby minimizing storage space in cardiovascular disease prediction.

This study shows encouraging predictive performance over different algorithms; however, real-world use requires optimization for computational efficiency, integration with electronic health records, and prospective validation on heterogeneous clinical cohorts. Extending utility to other data will require rigorous preprocessing, standardized feature selection, and continuous recalibrating of models to preserve accuracy and clinical relevance.

V. CONCLUSION

Cardiovascular disease (CVD) prediction is a critical endeavor aimed at identifying individuals at danger of rising conditions such as heart disease and stroke. MRI-RICR method facilitates early CVD prediction, thereby reducing the overall risk associated with CVD. Initially, the MRI-RICR method performs data preprocessing for addressing missing data and removing outliers, which contributes to minimizing the time complexity of CVD prediction. Subsequently, the method conducts dimensionality reduction

using Ruzicka indexive censored regression to select significant features with higher accuracy and precision. A comprehensive experimental evaluation is conducted, incorporating various parameters. Analyzed outcomes show that MRI-RICR method outperforms well existing approaches in attaining superior accuracy and precision. Moreover, MRI-RICR method proves to effective in reducing time consumption and space complexity for CVD forecast compared to conventional methods.

REFERENCES

[1] María Teresa García-Ordás, Martín Bayón-Gutiérrez, Carmen Benavides, Jose Aveleira-Mata & José Alberto Benítez-Andrades, "New cardiovascular disease prediction approach using support vector machine and quantum-behaved particle swarm optimization", Multimedia Tools and Applications, Springer, Volume 83, 2024, Pages 23901–23928. https://doi.org/10.1007/s11042-023-16194-z

[2] Marwa Obayya, Jamal M. Alsamri, Mohammed Abdullah Al-Hagery, Abdullah Mohammed, And Manar Ahmed Hamza, "Automated Cardiovascular Disease Diagnosis Using Honey Badger Optimization With Modified Deep Learning Model", IEEE Access, Volume 11, 2023, Pages 64272 – 64281. DOI: 10.1109/ACCESS.2023.3286661

[3] Nadiah A. Baghdadi, Sally Mohammed Farghaly Abdelaliem, Amer Malki, Ibrahim Gad, Ashraf Ewis & Elsayed Atlam, "Advanced machine learning techniques for cardiovascular disease early detection and diagnosis", Journal of Big Data, Springer, Volume 10, 2023, pages 1-29. https://doi.org/10.1186/s40537-023-00817-1

[4] Anil Pandurang Jawalkar, Pandla Swetcha, Nuka Manasvi, Pakki Sreekala, Samudrala Aishwarya, Potru Kanaka Durga Bhavani & Pendem Anjani, "Early prediction of heart disease with data analysis using supervised learning with stochastic gradient boosting", Journal of Engineering and Applied Science, Springer, Volume 70, 2023, Pages 1-18. https://doi.org/10.1186/s44147-023-00280-y

[5] Md. Imam Hossain, Mehadi Hasan Maruf, Md. Ashikur Rahman Khan, Farida Siddiqi Prity, Sharmin Fatema, Md. Sabbir Ejaz & Md. Ahnaf Sad Khan, "Heart disease prediction using distinct artificial intelligence techniques: performance analysis and comparison", Iran Journal of Computer Science, Springer, Volume 6, 2023, Pages 397–417. https://doi.org/10.1007/s42044-023-00148-7

[6] Abdullah Alqahtani , Shtwai Alsubai , Mohemmed Sha , Lucia Vilcekova, and Talha Javed, "Cardiovascular Disease Detection using Ensemble Learning", Computational Intelligence and Neuroscience, Hindawi, Volume 2022, August 2022, Pages 1-9. https://doi.org/10.1155/2022/5267498

[7] Osman Taylan, Abdulaziz S. Alkabaa, Hanan S. Alqabbaa, Esra Pamukçu and Víctor Leiva, "Early Prediction in Classification of Cardiovascular Diseases with Machine Learning, Neuro-Fuzzy and Statistical Methods", Biology, Volume 12, Issue 1, 2023, Pages 1-31. https://doi.org/10.3390/biology12010117

[8] Mohammad Mahbubur Rahman Khan Mamun and Tarek Elfouly, "Detection of Cardiovascular Disease from Clinical Parameters Using a One-Dimensional Convolutional Neural Network", Bioengineering, Volume 10, Issue 7, 2023, Pages 1-29. https://doi.org/10.3390/bioengineering10070796

[9] Abdallah Abdellatif, Hamdan Abdellatef, Jeevan Kanesan, Chee-Onn Chow, Joon Huang Chuah, And Hassan Muwafaq Gheni, "An Effective Heart Disease Detection and Severity Level Classification Model Using Machine Learning and Hyperparameter Optimization Methods", IEEE Access , Volume 10, 2022, Pages 79974 – 79985. DOI: 10.1109/ACCESS.2022.3191669

[10] Ninni Singh, Vinit Kumar Gunjan, Fahimuddin Shaik, Sudipta Roy , "Detection of Cardio Vascular abnormalities using gradient descent optimization and CNN", Health and Technology, Springer, Volume 14, 2024,Pages 155–168. https://doi.org/10.1007/s12553-023-00807-6

[11] Furqan Rustam, Abid Ishaq, Kashif Munir, Mubarak Almutairi, Naila Aslam and Imran Ashraf , "Incorporating CNN Features for Optimizing Performance of Ensemble Classifier for Cardiovascular Disease Prediction", Diagnostics, Volume 12, Issue 6, 2022, Pages 1-17. https://doi.org/10.3390/diagnostics12061474

[12] Sara Ghorashi, Khunsa Rehman, Anam Riaz, Hend Khalid Alkahtani, Ahmed H. Samak, Ivan Cherrez-Ojeda, and Amna Parveen, "Leveraging Regression Analysis to Predict Overlapping Symptoms of Cardiovascular Diseases", IEEE Access , Volume 11, 2023, Pages 60254 – 60266. DOI: 10.1109/ACCESS.2023.3286311

[13] Nidhi Sinha, M. A. Ganesh Kumar, Amit M. Joshi, and Linga Reddy Cenkeramaddi, "DASMcC: Data Augmented SMOTE Multi-Class Classifier for Prediction of Cardiovascular Diseases Using Time Series Features", IEEE Access, Volume 11, 2023, Pages 117643 – 117655. DOI: 10.1109/ACCESS.2023.3325705

[14] Ghulam Muhammad, Saad Naveed, Lubna Nadeem, Tariq Mahmood, Amjad R. Khan, Yasar Amin and Saeed Ali Omer Bahaj, "Enhancing Prognosis Accuracy for Ischemic Cardiovascular Disease Using K Nearest Neighbor Algorithm: A Robust Approach", IEEE Access , Volume 11, 2023, Pages 97879 – 97895. DOI: 10.1109/ACCESS.2023.3312046

[15] Marwa Obayya, Jamal M. Alsamri, Mohammed Abdullah Al-Hagery, Abdullah Mohammed, and Manar Ahmed Hamza, "Automated Cardiovascular Disease Diagnosis Using Honey Badger Optimization With Modified Deep Learning Model", IEEE Access , Volume 11, 2023, Pages 64272 – 64281. DOI: 10.1109/ACCESS.2023.3286661

[16] Mana Saleh A Reshan, Samina Amin, Muhammad Ali Zeb, Adel Sulaiman, Hani Alshahrani , and Asadullah Shaikh, "A Robust Heart Disease Prediction System Using Hybrid Deep Neural Networks", IEEE Access, Volume 11, 2023, Pages 121574 – 121591. DOI: 10.1109/ACCESS.2023.3328909

[17] Ambrish, Bharathi Ganesh, Anitha Ganesh, Chetana Srinivas, Dhanraj, Kiran Mensinkal, "Logistic regression technique for prediction of cardiovascular disease", Global Transitions Proceedings, Elsevier, Volume 3, Issue 1, June 2022, Pages 127-130. https://doi.org/10.1016/j.gltp.2022.04.008

[18] Kellen Sumwiza, Celestin Twizere, Gerard Rushingabigwi, Pierre Bakunzibake, Peace Bamurigire, "Enhanced cardiovascular disease prediction model using random forest algorithm", Informatics in Medicine Unlocked, Elsevier, Volume 41, Pages 1-9, 2023. https://doi.org/10.1016/j.imu.2023.101316

[19] Fuchen Li, Patrick Wu, Henry H. Ong, Josh F. Peterson, Wei-Qi Wei, Juan Zhao, "Evaluating and mitigating bias in machine learning models for cardiovascular disease prediction", Journal of Biomedical Informatics, Elsevier, Volume 138, 2023, Pages 1-7. https://doi.org/10.1016/j.jbi.2023.104294

[20] Giovanni Paragliola, Antonio Coronato, "An hybrid ECG-based deep network for the early identification of high-risk to major cardiovascular events for hypertension patients", Journal of Biomedical Informatics, Elsevier, Volume 113, 2021, Pages 1-10. https://doi.org/10.1016/j.jbi.2020.103648

[21] Sadia Arooj, Saif ur Rehman, Azhar Imran, Abdullah Almuhaimeed, A. Khuzaim Alzahrani and Abdulkareem Alzahrani, "A Deep Convolutional Neural Network for the Early Detection of Heart Disease", Biomedicines, Volume 10, Issue 11, 2022, Pages 1-15. https://doi.org/10.3390/biomedicines10112796