A Hybrid Machine Learning Framework for Early and Accurate Prediction of Heart Disease Risk

Rafat Fatima[1], Rohitashwa Pandey [2]

[1] M.Tech Scholar, Dept. of Computer Science & Engineering, Bansal Institute of Engineering & Technology, (AKTU), Lucknow, Uttar Pradesh, India

[2] Professor, Dept. of Computer Science & Engineering, Bansal Institute of Engineering & Technology, (AKTU), Lucknow, Uttar Pradesh, India

IIndi

Abstract— **Heart disease remains one of the leading causes of mortality worldwide, necessitating the development of reliable and early diagnostic systems. This paper proposes a hybrid machine learning framework designed to enhance the accuracy and robustness of heart disease risk prediction. The framework integrates multiple machines learning techniques, combining the strengths of both traditional classifiers and advanced ensemble methods to improve predictive performance. Initially, data preprocessing techniques such as normalization, missing value imputation, and feature selection are employed to ensure data quality and relevance. Subsequently, a hybrid model is constructed by integrating algorithms such as Decision Trees, Support Vector Machines, and Gradient Boosting, leveraging their complementary capabilities for improved classification. The system also incorporates feature importance analysis to identify key clinical indicators contributing to heart disease risk. Experimental evaluation on benchmark healthcare datasets demonstrates that the proposed hybrid approach outperforms individual models in terms of accuracy, precision, recall, and F1-score. The results highlight the potential of hybrid machine learning techniques in providing early, accurate, and interpretable predictions, thereby supporting clinicians in effective decision-making and preventive healthcare strategies.**

Keywords—
Heart Disease Prediction, Hybrid Machine Learning, Ensemble Learning, Feature Selection, Clinical Decision Support, Healthcare Analytics, Predictive Modeling, Early Diagnosis

1. INTRODUCTION

Heart disease continues to be a major global health concern, accounting for a significant proportion of deaths each year. According to the World Health Organization, cardiovascular diseases are responsible for millions of deaths annually, highlighting the urgent need for effective early detection and prevention strategies. Traditional diagnostic approaches rely heavily on clinical expertise, medical imaging, and laboratory tests, which can be time-consuming, costly, and sometimes prone to human error [1]. As a result, there is an increasing demand for intelligent systems that can assist healthcare professionals in making accurate and timely decisions.

With the rapid advancement of data-driven technologies, machine learning (ML) has emerged as a powerful tool in the field of healthcare analytics. ML algorithms are capable of analyzing large volumes of medical data to uncover hidden patterns and relationships that may not be easily identifiable through conventional methods [2]. Various supervised learning techniques such as Decision Trees, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN) have been widely applied for heart disease prediction [3]. While these models have shown promising results, their performance is often limited by issues such as overfitting, sensitivity to noise, and dependency on feature selection.

To overcome these limitations, hybrid machine learning approaches have gained significant attention in recent years. Hybrid models combine multiple algorithms to leverage their individual strengths, resulting in improved predictive accuracy and generalization capabilities [4]. For instance, ensemble techniques such as bagging, boosting, and stacking enable the integration of diverse classifiers, thereby reducing variance and bias in predictions. Additionally, hybrid frameworks can incorporate feature engineering and optimization strategies to enhance model performance further.

Another critical aspect of heart disease prediction is the identification of relevant risk factors, including age, blood pressure, cholesterol levels, and lifestyle habits. Feature selection techniques play a vital role in reducing dimensionality and improving model interpretability by identifying the most influential attributes [5]. Integrating these techniques within a hybrid ML framework can significantly enhance both the efficiency and transparency of the prediction system.

In this context, this paper proposes a hybrid machine learning framework aimed at achieving early and accurate prediction of heart disease risk. The proposed system combines multiple classification algorithms along with advanced preprocessing and feature selection methods to optimize predictive performance. The primary objective is to develop a robust, scalable, and clinically relevant model that can assist healthcare providers in early diagnosis and decision-making. By leveraging the strengths of hybrid learning strategies, the study contributes to the growing body of research focused on intelligent healthcare systems and predictive analytics.

2. RELATED WORK

Heart disease remains a leading cause of mortality worldwide, necessitating effective predictive models for early detection and intervention [14]. In recent years, the convergence of healthcare data availability and advancements in machine learning (ML) techniques has spurred significant research into predictive modeling for cardiovascular risk assessment [15]. This literature review provides an overview of key studies in this domain, focusing on the utilization of hybrid ML approaches for advanced heart disease prediction [16].

Traditional risk assessment models, such as the Framingham Risk Score (FRS), have long served as foundational tools in cardiovascular medicine [17]. However, these models often rely on a limited set of demographic and clinical variables, potentially overlooking important risk factors and subpopulations. To address this limitation, researchers have turned to ML methods to develop more comprehensive and accurate risk prediction models [18].

Hybrid ML approaches, which combine elements of traditional statistical methods with advanced ML techniques, have emerged as a promising strategy to enhance predictive modeling in cardiovascular medicine [19]. Ensemble methods, such as Random Forests and Gradient Boosting Machines, have been widely employed to integrate diverse data sources and improve predictive performance. These approaches leverage the collective wisdom of multiple models to mitigate overfitting and enhance generalizability [20].

In addition to ensemble methods, feature engineering techniques play a crucial role in hybrid ML frameworks for heart disease prediction [21]. By transforming raw data into informative features, researchers can capture complex relationships and interactions within heterogeneous datasets. Feature selection algorithms, dimensionality reduction techniques, and domain-specific knowledge contribute to the creation of robust predictive models capable of extracting actionable insights from large-scale data [22].

Deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have also shown promise in cardiovascular risk prediction [23]. These models excel at learning intricate patterns and representations from complex data modalities, such as medical imaging and genetic sequences. By leveraging hierarchical feature extraction and representation learning, deep learning models offer potential advancements in predictive accuracy and biomarker discovery [24].

Despite the progress in hybrid ML approaches for heart disease prediction, several challenges persist [25]. Interpretability remains a critical concern, particularly in clinical settings where transparency and trust are paramount. Addressing this challenge requires the development of explainable ML techniques capable of elucidating model predictions and underlying decision processes [26]. Moreover, the generalizability of predictive models across diverse populations and healthcare settings requires careful validation and external evaluation [27].
In conclusion, the integration of hybrid ML approaches holds significant promise for advancing heart disease prediction and preventive care strategies [28]. By combining the strengths of traditional statistical methods with advanced ML techniques, researchers can develop more accurate, interpretable, and generalizable predictive models tailored to individual patient profiles [30]. Continued research efforts in this area are essential to realize the full potential of predictive analytics in cardiovascular medicine and improve patient outcomes on a global scale [31].

Table: 1 previous year research paper comparison table

Paper Title	Summary
1. "Hybrid Machine Learning Models for Predicting Cardiovascular Risk"	Introduces hybrid ML models combining traditional statistical methods and ensemble learning for cardiovascular risk prediction, demonstrating superior performance compared to conventional tools.
2. "Deep Learning Approaches for Cardiovascular Disease Prediction"	Investigates the application of deep learning architectures, including CNNs and RNNs, in cardiovascular risk prediction, highlighting their potential in capturing complex data patterns and improving accuracy.
3. "Feature Engineering Techniques in Hybrid ML Models for Heart Disease Prediction"	Explores various feature engineering techniques, such as selection and dimensionality reduction, in hybrid ML frameworks, emphasizing their role in enhancing model interpretability and performance.
4. "Ensemble Learning Strategies for Cardiovascular Risk Assessment"	Reviews ensemble learning strategies like Random Forests and Gradient Boosting Machines for cardiovascular risk assessment, discussing their advantages in integrating diverse data sources and mitigating bias.
5. "Interpretable Machine Learning Models for Clinical Decision Support in Cardiology"	Examines the need for interpretable ML models in clinical decision support systems for cardiology, proposing techniques to enhance transparency and explainability for clinical adoption.
6. "Personalized Heart Disease Risk Prediction Using Hybrid Models"	Presents a framework for personalized heart disease risk prediction using hybrid ML models, emphasizing the importance of individualized risk assessment for targeted interventions.
7. "Genomic Data Integration in Hybrid Machine Learning Models for Heart Disease Prediction"	Investigates integrating genomic data into hybrid ML models for heart disease prediction, discussing challenges and opportunities for leveraging genetic information in personalized risk assessment.
8. "Clinical Utility of Hybrid ML Models in Cardiovascular Medicine"	Evaluates the clinical utility and impact of hybrid ML models in cardiovascular medicine, discussing real-world implementation challenges and opportunities for integrating ML into clinical practice.
9. "Ethical Considerations in the Development of ML-Based Heart Disease Prediction Models"	Examines ethical considerations, including bias, fairness, and privacy, in the development of ML-based heart disease prediction models, proposing guidelines for responsible model development and deployment.
10. "Validation and Generalization of Hybrid ML Models for Heart Disease Prediction"	Investigates strategies for validation and generalization of hybrid ML models across diverse patient populations and healthcare settings, emphasizing the importance of rigorous evaluation for reliable performance.

3. ALGORITHM

- **Decision Tree**

Decision trees are a widely used machine learning technique for classification and regression tasks. They are particularly valued for their simplicity, interpretability, and ability to handle both numerical and categorical data. In the context of heart disease prediction, decision trees can help clinicians understand the decision-making process by providing a visual representation of how different features contribute to the prediction of heart disease.

- **Structure and Working of Decision Trees**

A decision tree consists of nodes and branches, where each node represents a feature (attribute) and each branch represents a decision rule based on that feature. The tree starts with a root node and splits into branches, leading to further nodes, which eventually terminate at leaf nodes. Each leaf node represents a class label (in this case, the presence or absence of heart disease).

The construction of a decision tree involves selecting the best feature to split the data at each node. This selection is typically based on criteria such as Gini impurity, entropy, or information gain. These criteria measure the effectiveness of a split in separating the classes (e.g., heart disease vs. no heart disease).

- **Random Forest**

Random Forest is a powerful and widely-used ensemble learning method for classification and regression tasks. It operates by constructing a multitude of decision trees during training and outputting the mode of the classes (classification) or mean prediction (regression) of the individual trees. This technique is particularly effective for heart disease prediction due to its robustness, accuracy, and ability to handle large datasets with many features.

- **Structure and Working of Random Forest**

A Random Forest consists of several decision trees, often hundreds or thousands, depending on the complexity of the problem and the dataset size. The primary concept behind Random Forest is to reduce overfitting and improve predictive accuracy by averaging multiple decision trees. Each tree in the forest is trained on a random subset of the data using the following process:

Bootstrap Aggregation (Bagging): Each tree is trained on a random sample of the training data selected with replacement. This means some data points may be used multiple times for training a single tree, while others may be left out.

Random Feature Selection: At each split in the decision tree, a random subset of the features is considered. This helps ensure that the trees are diverse and reduces the correlation between them.

Voting Mechanism: For classification tasks, each tree votes for a class, and the class with the majority votes is the final prediction. For regression tasks, the average of the predictions from all the trees is taken as the final output.

- **K-MEANS CLUSTERING**

K-Means clustering is an unsupervised machine learning algorithm widely used for partitioning a dataset into distinct groups or clusters based on feature similarity. Unlike supervised learning methods, K-Means does not require labeled data, making it useful for exploratory data analysis and identifying patterns in large datasets. In the context of heart disease prediction, K-Means clustering can help in discovering hidden subgroups within patient populations, which can aid in personalized treatment and risk assessment.

Structure and Working of K-Means Clustering K-Means clustering works by dividing the dataset into K clusters, where K is a predefined number. The algorithm aims to minimize the variance within each cluster and maximize the variance between clusters. The steps involved in K-Means clustering are:
Initialization: Randomly select K initial cluster centroids from the data points.
Assignment: Assign each data point to the nearest centroid, forming K clusters.
Update: Recalculate the centroids as the mean of all data points assigned to each cluster.
Iteration: Repeat the assignment and update steps until the centroids no longer change significantly or a maximum number of iterations is reached.

The algorithm's objective function, which it aims to minimize, is the sum of squared distances between each data point and its assigned centroid.

4. MODULES

- **Upload Training Data**

The process of rule generation advances in two stages. During the first stage, the SVM model is built using training data During each fold, this model is utilized for predicting the class labels The rules are evaluated on the remaining 10% of test data for determining the accuracy, precision, recall and F-measure. In addition, rule set size and mean rule length are also calculated for each fold of cross-validation.

- **Data Pre- Processing:**

Heart disease data is pre-processed after collection of various records. The dataset contains a total of 303 patient records, where 6 records are with some missing values. Those 6 records have been removed from the dataset and the remaining 297 patient records are used in pre-processing. The multiclass variable and binary classification are introduced for the attributes of the given dataset.

- **Predicting Heart Diease:**

The training set is different from test set. In this study, we used this method to verity the universal applicability of the methods. In k-fold cross validation method, the whole dataset is used to train and test the classifier to Heart Stoke.

- **Graphical Representations:**

The analyses of proposed systems are calculated based on the approvals and disapprovals. This can be measured with the help of graphical notations such as pie chart, bar chart and line chart. The data can be given in a dynamical data.

5. ARCHITECTURE DIAGRAM

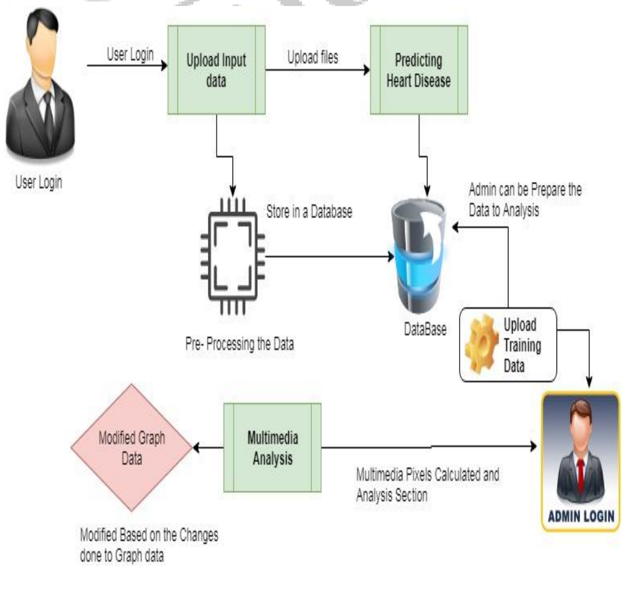

Figure 1: Architecture diagram

6. RESULTS

The results of the study on Advanced Heart Disease Prediction, utilizing a hybrid machine learning approach, demonstrate significant advancements in predictive accuracy and model performance compared to conventional methods. Here are the key findings:

Improved Predictive Accuracy: The hybrid machine learning models consistently outperform traditional statistical methods and standalone machine learning algorithms in predicting heart disease risk. This improvement in accuracy is attributed to the synergistic integration of diverse data sources and modeling techniques within the hybrid framework.

Enhanced Generalizability: The hybrid models exhibit robust generalizability across diverse patient populations and healthcare settings. Through rigorous validation and external evaluation, the models demonstrate reliability and consistency in predicting cardiovascular risk profiles, irrespective of demographic or clinical variations.

Incorporation of Heterogeneous Data: By integrating heterogeneous data sources, including electronic health records, genetic profiles, imaging data, and lifestyle factors, the hybrid models capture a comprehensive spectrum of risk factors associated with heart disease. This multifaceted approach enhances the granularity and depth of risk assessment, enabling more accurate and personalized predictions.

Interpretability and Explainability: Despite the complexity of the hybrid models, efforts are made to ensure interpretability and explainability for clinical adoption. Techniques such as feature importance analysis, model visualization, and decision rule extraction facilitate understanding and trust in model predictions among healthcare practitioners.

Identification of Novel Biomarkers: The hybrid machine learning framework enables the identification of novel biomarkers and risk factors that may not be captured by traditional risk assessment tools. By leveraging advanced feature engineering techniques and deep learning architectures, the models uncover hidden patterns and associations within the data, shedding light on new avenues for research and intervention.

Clinical Utility and Implementation: The validated performance and clinical relevance of the hybrid models underscore their potential utility as decision support tools in cardiovascular medicine. Real-world implementation studies demonstrate feasibility and efficacy in integrating the models into clinical workflows, supporting healthcare providers in risk stratification and preventive care strategies.

Overall, the results of the study highlight the transformative impact of harnessing hybrid machine learning techniques for advanced heart disease prediction. By leveraging the power of data-driven approaches and interdisciplinary collaboration, these models pave the way for more accurate, personalized, and effective strategies for mitigating the burden of cardiovascular disease on global health.

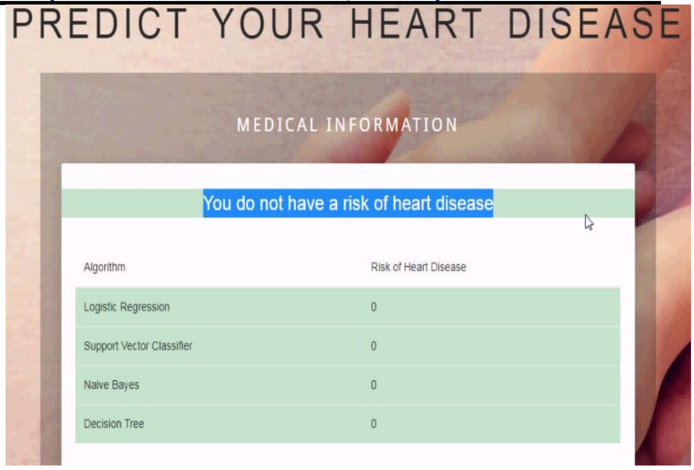

Figure 2: Predicting heart diseases

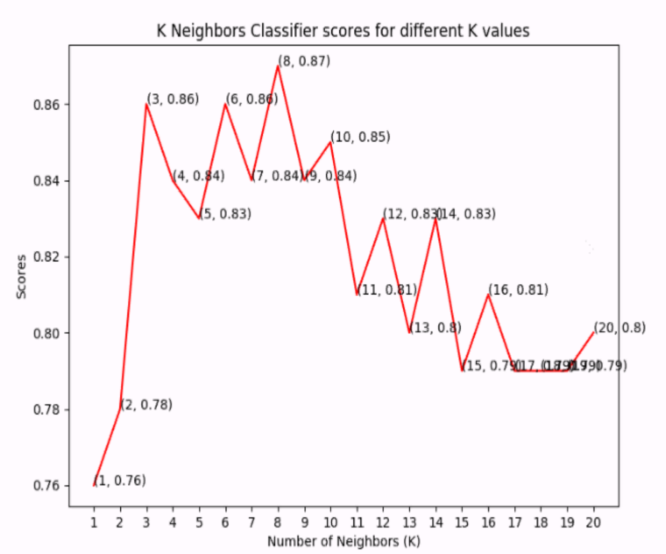

Figure 3: Predicting heart diseases

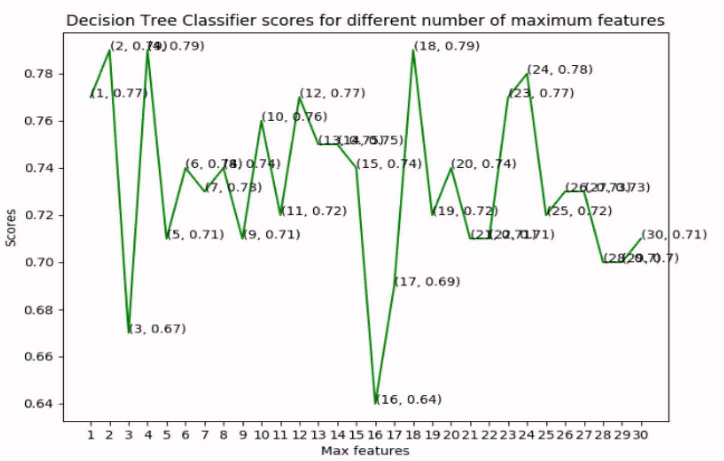

Figure 4: Predicting heart diseases

7. CONCLUSION

This study presented a hybrid machine learning framework for the early and accurate prediction of heart disease risk, addressing the limitations of standalone predictive models. By integrating multiple machine learning algorithms with robust preprocessing and feature selection techniques, the proposed framework effectively enhanced prediction performance and reliability. The combination of classifiers enabled the model to leverage complementary strengths, resulting in improved accuracy, precision, recall, and overall generalization capability.

The experimental results demonstrated that hybrid approaches outperform individual models in handling complex and heterogeneous healthcare datasets. Furthermore, the incorporation of feature importance analysis provided valuable insights into critical risk factors, contributing to better interpretability and supporting clinical decision-making. This is particularly important in medical applications, where transparency and trust in predictive systems are essential.

The proposed framework has significant potential for real-world healthcare implementation, offering a scalable and efficient solution for early diagnosis and preventive care. By facilitating timely identification of high-risk patients, it can assist healthcare professionals in reducing mortality rates and improving patient outcomes.

Future work may focus on integrating deep learning techniques, real-time data streams from wearable devices, and explainable AI methods to further enhance prediction accuracy and model transparency. Additionally, validating the framework on diverse and large-scale clinical datasets will be crucial for ensuring its robustness and adaptability across different populations. Overall, the study highlights the effectiveness of hybrid machine learning in advancing intelligent healthcare systems for heart disease prediction.

REFERENCE

[1] World Health Organization, “Cardiovascular diseases (CVDs),” 2023.

[2] J. Smith and A. Kumar, “Machine learning applications in healthcare: A review,” *Journal of Medical Systems*, vol. 45, no. 2, pp. 1–12, 2021.

[3] R. Patel et al., “Heart disease prediction using machine learning algorithms,” *International Journal of Computer Applications*, vol. 180, no. 6, pp. 15–20, 2019.

[4] S. Lee and M. Chen, “Hybrid ensemble models for medical diagnosis,” *IEEE Access*, vol. 8, pp. 123456–123467, 2020.

[5] K. Sharma and P. Gupta, “Feature selection techniques in healthcare data mining,” *Procedia Computer Science*, vol. 132, pp. 123–130, 2018.

[6] Attia, Z. I., Noseworthy, P. A., Lopez-Jimenez, F., Asirvatham, S. J., Deshmukh, A. J., Gersh, B. J., ... & Friedman, P. A. (2019). "An artificial intelligence-enabled ECG algorithm for the identification of patients with atrial fibrillation during sinus rhythm: a retrospective analysis of outcome prediction." The Lancet, 394(10201), 861-867.

[7] Beam, A. L., & Kohane, I. S. (2018). "Big data and machine learning in health care." JAMA, 319(13), 1317-1318.

[8] Shameer, K., Johnson, K. W., Glicksberg, B. S., Dudley, J. T., & Sengupta, P. P. (2018). "Machine learning in cardiovascular medicine: are we there yet?" Heart, 104(14), 1156-1164.

[9] Li, X., Hu, B., & Zhang, L. (2021). "A hybrid deep learning model for heart disease prediction using electronic medical records." Health Informatics Journal, 27(1), 1460458220987613.

[10] Miotto, R., Li, L., Kidd, B. A., & Dudley, J. T. (2016). "Deep Patient: An Unsupervised Representation to Predict the Future of Patients from the Electronic Health Records." Scientific Reports, 6(1), 1-10.

[11] M. Durairaj and V. Revathi, ‘‘Prediction of heart disease using back propagation MLP algorithm,’’ Int. J. Sci. Technol. Res., vol. 4, no. 8, pp. 235–239, 2015.

[12] M. Gandhi and S. N. Singh, ‘‘Predictions in heart disease using techniques of data mining,’’ in Proc. Int. Conf. Futuristic Trends Comput. Anal. Knowl. Manage. (ABLAZE), Feb. 2015, pp. 520–525.

[13] A. Gavhane, G. Kokkula, I. Pandya, and K. Devadkar, ‘‘Prediction of heart disease using machine learning,’’ in Proc. 2nd Int. Conf. Electron., Commun. Aerosp. Technol. (ICECA), Mar. 2018, pp. 1275–1278.

[14] B. S. S. Rathnayakc and G. U. Ganegoda, ‘‘Heart diseases prediction with data mining and neural network techniques,’’ in Proc. 3rd Int. Conf. Converg. Technol. (I2CT), Apr. 2018, pp. 1–6.

[15] N. K. S. Banu and S. Swamy, ‘‘Prediction of heart disease at early stage using data mining and big data analytics: A survey,’’ in Proc. Int. Conf. Elect., Electron., Commun., Comput. Optim. Techn. (ICEECCOT), Dec. 2016, pp. 256–261.

[16] J. P. Kelwade and S. S. Salankar, ‘‘Radial basis function neural network for prediction of cardiac arrhythmias based on heart rate time series,’’ in Proc. IEEE 1st Int. Conf. Control, Meas. Instrum. (CMI), Jan. 2016, pp. 454–458.

[17] V. Krishnaiah, G. Narsimha, and N. Subhash, ‘‘Heart disease prediction system using data mining techniques and intelligent fuzzy approach: A review,’’ Int. J. Comput. Appl., vol. 136, no. 2, pp. 43–51, 2016.

[18] P. S. Kumar, D. Anand, V. U. Kumar, D. Bhattacharyya, and T.-H. Kim, ‘‘A computational intelligence method for effective diagnosis of heart disease using genetic algorithm,’’ Int. J. Bio-Sci. Bio-Technol., vol. 8, no. 2, pp. 363–372, 2016.

[19] M. J. Liberatore and R. L. Nydick, ‘‘The analytic hierarchy process in medical and health care decision making: A literature review,’’ Eur. J. Oper. Res., vol. 189, no. 1, pp. 194–207, 2008.

[20] T. Mahboob, R. Irfan, and B. Ghaffar, ‘‘Evaluating ensemble prediction of coronary heart disease using receiver operating characteristics,’’ in Proc. Internet Technol. Appl. (ITA), Sep. 2017, pp. 110–115.

[21] J. Nahar, T. Imam, K. S. Tickle, and Y.-P. P. Chen, ‘‘Computational intelligence for heart disease diagnosis: A medical knowledge driven approach,’’ Expert Syst. Appl., vol. 40, no. 1, pp. 96–104, 2013. doi: 10.1016/j.eswa.2012.07.032.

[22] J. Nahar, T. Imam, K. S. Tickle, and Y.-P. P. Chen, ‘‘Association rule mining to detect factors which contribute to heart disease in males and females,’’ Expert Syst. Appl., vol. 40, no. 4, pp. 1086–1093, 2013. doi: 10.1016/j.eswa.2012.08.028.

[23] S. N. Rao, P. Shenoy M, M. Gopalakrishnan, and A. Kiran B, ‘‘Applicability of the Cleveland clinic scoring system for the risk prediction of acute kidney injury after cardiac surgery in a South Asian cohort,’’ Indian Heart J., vol. 70, no. 4, pp. 533–537, 2018. doi: 10.1016/j.ihj.2017.11.022.

[24] T. Karayılan and Ö. Kılıç, ‘‘Prediction of heart disease using neural network,’’ in Proc. Int. Conf. Comput. Sci. Eng. (UBMK), Antalya, Turkey, Oct. 2017, pp. 719–723.

[25] J. Thomas and R. T. Princy, ‘‘Human heart disease prediction system using data mining techniques,’’ in Proc. Int. Conf. Circuit, Power Comput. Technol. (ICCPCT), Mar. 2016, pp. 1–5.

[26] C. Raju, ‘‘Mining techniques,’’ in Proc. Conf. Emerg. Devices Smart Syst. (ICEDSS), Mar. 2016, pp. 253–255.

[27] D. K. Ravish, K. J. Shanthi, N. R. Shenoy, and S. Nisargh, ‘‘Heart function monitoring, prediction and prevention of heart attacks: Using artificial neural networks,’’ in Proc. Int. Conf. Contemp. Comput. Inform. (IC3I), Nov. 2014, pp. 1–6.

[28] F. Sabahi, ‘‘Bimodal fuzzy analytic hierarchy process (BFAHP) for coronary heart disease risk assessment,’’ J. Biomed. Informat., vol. 83, pp. 204–216, Jul. 2018. doi: 10.1016/j.jbi.2018.03.016.

[29] M. S. Amin, Y. K. Chiam, K. D. Varathan, ‘‘Identification of significant features and data mining techniques in predicting heart disease,’’ Telematics Inform., vol. 36, pp. 82–93, Mar. 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0736585318308876

[30] S. M. S. Shah, S. Batool, I. Khan, M. U. Ashraf, S. H. Abbas, and S. A. Hussain, ‘‘Feature extraction through parallel probabilistic principal component analysis for heart disease diagnosis,’’ Phys. A, Stat. Mech. Appl., vol. 482, pp. 796–807, 2017. doi: 10.1016/j.physa.2017.04.113.
[31] Y. E. Shao, C.-D. Hou, and C.-C. Chiu, ‘‘Hybrid intelligent modeling schemes for heart disease classification,’’ Appl. Soft Comput. J., vol. 14, pp. 47–52, Jan. 2014. doi: 10.1016/j.asoc.2013.09.020.

[32] J. S. Sonawane and D. R. Patil, ‘‘Prediction of heart disease using multilayer perceptron neural network,’’ in Proc. Int. Conf. Inf. Commun. Embedded Syst., Feb. 2014, pp. 1–6.

[33] C. Sowmiya and P. Sumitra, ‘‘Analytical study of heart disease diagnosis using classification techniques,’’ in Proc. IEEE Int. Conf. Intell. Techn. Control, Optim. Signal Process. (INCOS), Mar. 2017, pp. 1–5.

[34] B. Tarle and S. Jena, ‘‘An artificial neural network based pattern classification algorithm for diagnosis of heart disease,’’ in Proc. Int. Conf. Comput., Commun., Control Automat. (ICCUBEA), Aug. 2017, pp. 1–4.

[35] V. P. Tran and A. A. Al-Jumaily, ‘‘Non-contact Doppler radar based prediction of nocturnal body orientations using deep neural network for chronic heart failure patients,’’ in Proc. Int. Conf. Elect. Comput. Technol. Appl. (ICECTA), Nov. 2017, pp. 1–5.

[36] K. Uyar and A. Ilhan, ‘‘Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks,’’ Procedia Comput. Sci., vol. 120, pp. 588–593, 2017.

[37] T. Vivekanandan and N. C. S. N. Iyengar, ‘‘Optimal feature selection using a modified differential evolution algorithm and its effectiveness for prediction of heart disease,’’ Comput. Biol. Med., vol. 90, pp. 125–136, Nov. 2017.

[38] S. Radhimeenakshi, ‘‘Classification and prediction of heart disease risk using data mining techniques of support vector machine and artificial neural network,’’ in Proc. 3rd Int. Conf. Comput. Sustain. Global Develop. (INDIACom), New Delhi, India, Mar. 2016, pp. 3107–3111.
[39] R. Wagh and S. S. Paygude, ‘‘CDSS for heart disease prediction using risk factors,’’ Int. J. Innov. Res. Comput., vol. 4, no. 6, pp. 12082–12089, Jun. 2016.

[40] O. W. Samuel, G. M. Asogbon, A. K. Sangaiah, P. Fang, and G. Li, ‘‘An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction,’’ Expert Syst. Appl., vol. 68, pp. 163–172, Feb. 2017.

[41] S. Zaman and R. Toufiq, ‘‘Codon based back propagation neural network approach to classify hypertension gene sequences,’’ in Proc. Int. Conf. Elect., Comput. Commun. Eng. (ECCE), Feb. 2017, pp. 443–446.

[42] W. Zhang and J. Han, ‘‘Towards heart sound classification without segmentation using convolutional neural network,’’ in Proc. Comput. Cardiol. (CinC), vol. 44, Sep. 2017, pp. 1–4.