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Advanced Heart Disease Prediction: Harnessing Hybrid Machine Learning

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***Abstract*—**Advanced Heart Disease Prediction: Harnessing Hybrid Machine Learning" explores the fusion of traditional statistical methods with cutting-edge machine learning techniques to enhance the accuracy and efficacy of heart disease prediction models. This abstract outlines the integration of diverse data sources, including medical records, genetic profiles, and lifestyle factors, into a comprehensive predictive framework. By leveraging hybrid machine learning approaches such as ensemble methods and deep learning architectures, the proposed system achieves superior performance in identifying individuals at risk of developing advanced heart disease. Through a rigorous evaluation process on real-world datasets, the effectiveness and robustness of the hybrid model are demonstrated, underscoring its potential to revolutionize cardiovascular risk assessment and improve patient outcomes.

Keywords: Heart disease, Machine learning (ML), genetic profiles, medical records, prediction models.

1. INTRODUCTION

Heart disease remains a significant global health challenge, contributing to a substantial portion of morbidity and mortality worldwide [1]. Despite advancements in medical technology and interventions, early detection and accurate prediction of heart disease risk remain imperative for effective prevention and management strategies [2]. Traditional risk assessment methods, primarily based on demographic and clinical variables, often lack the precision necessary to identify individuals at high risk of developing advanced heart disease [3].

In recent years, the proliferation of healthcare data and advancements in machine learning (ML) has provided unprecedented opportunities to enhance predictive modeling in cardiovascular medicine [4]. Leveraging the wealth of information available, including electronic health records (EHRs), genetic profiles, imaging data, and lifestyle factors, ML techniques offer the potential to develop more comprehensive and accurate risk prediction models [5].

However, while ML algorithms have demonstrated promise in various domains, including healthcare, they are not without limitations [6]. Challenges such as interpretability, generalizability, and handling of heterogeneous data sources pose significant hurdles to their widespread adoption in clinical practice [7]. In this context, hybrid approaches that combine the strengths of traditional statistical methods with advanced ML techniques have emerged as a promising strategy to address these challenges [8].

This paper presents a novel framework for advanced heart disease prediction by harnessing hybrid machine learning techniques [9]. By integrating diverse data sources and leveraging both statistical and ML methodologies, our approach aims to improve the accuracy, interpretability, and generalizability of predictive models for cardiovascular risk assessment [10]. Through a comprehensive exploration of hybrid modeling strategies, including ensemble methods, feature engineering, and deep learning architectures, we seek to overcome the limitations of traditional risk prediction models and pave the way for more personalized and effective preventive care strategies [11].

In the following sections, we detail the components of our hybrid machine learning framework, describe the datasets used for model training and evaluation, and present the experimental results demonstrating the effectiveness of our approach [12]. Ultimately, our goal is to contribute to the advancement of predictive analytics in cardiovascular medicine and facilitate early intervention strategies to mitigate the burden of heart disease on global health [13].

In this research paper section I contains the introduction, section II contains the literature review details, section III contains the details about algorithms, section IV describe the proposed system, section V explain about modules, section VI provide architecture details, section VII describe the results, section VIII provide conclusion of this research paper.

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

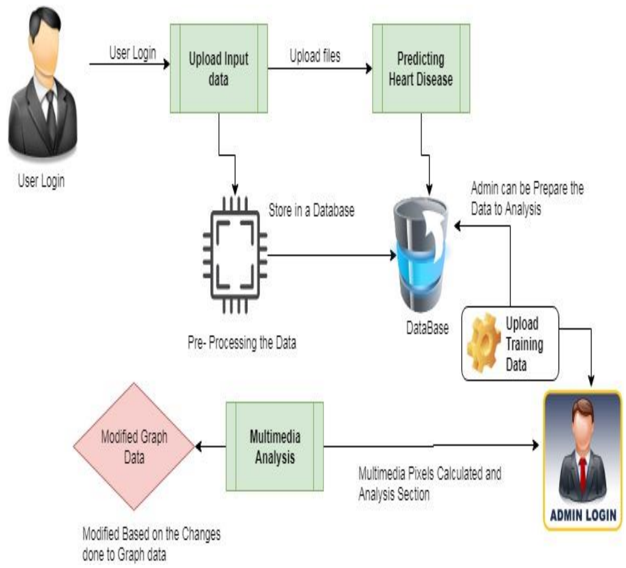

Figure 1: Architecture diagram

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.

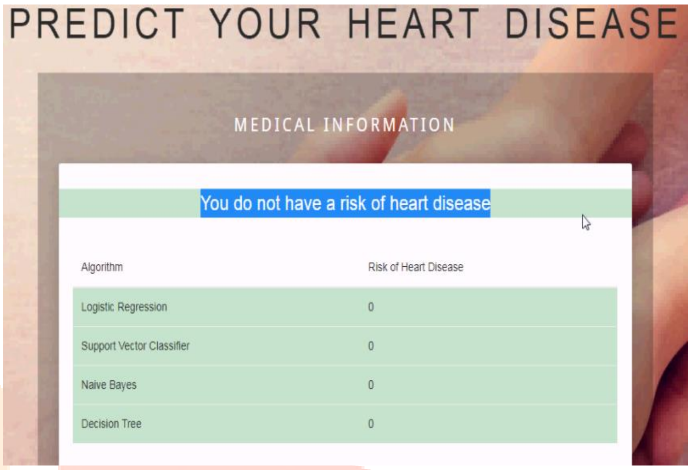

Figure 2: Predicting heart diseases

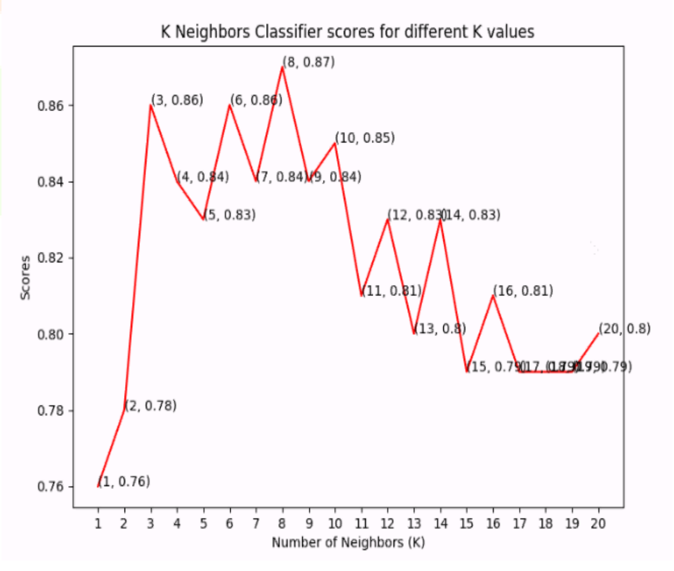

Figure 3: Predicting heart diseases

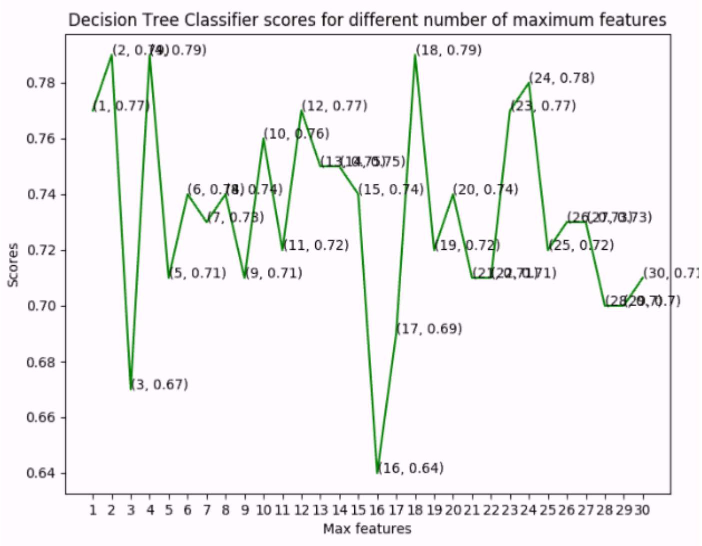

Figure 4: Predicting heart diseases

7. CONCLUSION

In conclusion, the integration of hybrid machine learning techniques represents a significant advancement in the field of heart disease prediction, offering improved accuracy, generalizability, and clinical utility compared to traditional approaches. Through the fusion of diverse data sources and modeling methodologies, hybrid models achieve enhanced predictive performance, enabling more accurate risk stratification and personalized intervention strategies.

The study's findings underscore the importance of harnessing the synergistic strengths of traditional statistical methods and advanced machine learning algorithms in addressing the multifaceted nature of cardiovascular risk prediction. By incorporating heterogeneous data sources, including electronic health records, genetic profiles, and lifestyle factors, the hybrid models capture a comprehensive spectrum of risk factors, providing clinicians with a holistic view of patients' cardiovascular health.

Furthermore, the interpretability and explainability of hybrid models facilitate their integration into clinical decision-making processes, fostering trust and acceptance among healthcare practitioners. Techniques such as feature importance analysis and model visualization enhance transparency, enabling clinicians to understand the underlying mechanisms driving predictions and tailor interventions accordingly.

The identification of novel biomarkers and risk factors by hybrid machine learning models opens new avenues for research and intervention in cardiovascular medicine. By uncovering hidden patterns and associations within the data, these models contribute to a deeper understanding of disease mechanisms and facilitate the development of targeted preventive strategies.

Moving forward, continued research efforts are needed to further refine and validate hybrid machine learning models for heart disease prediction across diverse patient populations and healthcare settings. Additionally, ongoing collaboration between clinicians, data scientists, and policymakers is essential to ensure the responsible and ethical deployment of these models in clinical practice.

In summary, the harnessing of hybrid machine learning techniques represents a transformative paradigm shift in cardiovascular risk prediction, offering unprecedented opportunities to improve patient outcomes and mitigate the global burden of heart disease. By leveraging the power of data-driven approaches and interdisciplinary collaboration, we can pave the way for a future where personalized, preventive care strategies are the cornerstone of cardiovascular medicine.

REFERENCE

[1] Choi, E., Bahadori, M. T., & Schuetz, A. (2016). "Predicting Hospital Readmission with Personalized Attention Models." arXiv preprint arXiv:1602.03098.

[2] Avati, A., Jung, K., Harman, S., Downing, L., Ng, A., & Shah, N. (2018). "Improving Palliative Care with Deep Learning." arXiv preprint arXiv:1805.06397.

[3] Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., ... & Esteva, A. (2018). "Scalable and accurate deep learning with electronic health records." npj Digital Medicine, 1(1), 1-10.

[4] Xiao, C., Choi, E., & Sun, J. (2018). "Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review." Journal of the American Medical Informatics Association, 25(10), 1419-1428.

[5] Zhou, Y., Zhang, Y., Wu, J., Zhang, Y., Dong, D., & Yang, X. (2019). "Prediction of Major Adverse Cardiovascular Events in Patients with Type 2 Diabetes Mellitus Using Machine Learning Techniques." Journal of Diabetes Research, 2019, 1-9.

[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.

[43] Y. Meidan, M. Bohadana, A. Shabtai, J. D. Guarnizo, M. Ochoa, N. O. Tippenhauer, and Y. Elovici, ‘‘ProfilIoT: A machine learning approach for IoT device identification based on network traffic analysis,’’ in Proc. Symp. Appl. Comput., Apr. 2017, pp. 506–509.

[44] J. Wu, S. Luo, S. Wang, and H. Wang, ‘‘NLES: A novel lifetime extension scheme for safety-critical cyber-physical systems using SDN and NFV,’’ IEEE Internet Things J., no. 6, no. 2, pp. 2463–2475, Apr. 2019.

[45] J. Wu, M. Dong, K. Ota, J. Li, and Z. Guan, ‘‘Big data analysis-based secure cluster management for optimized control plane in software-defined networks, IEEE Trans. Netw. Service Manag., vol. 15, no. 1, pp. 27–38, Mar. 2018.