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Artificial Intelligence-Based Models for Predicting Cardiovascular Events: A Review of Current Trends and Future Directions

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Abstract— Cardiovascular diseases (CVDs) remain a leading cause of mortality globally, necessitating effective risk prediction models for early identification and intervention. In recent years, artificial intelligence (AI) has emerged as a promising tool for predicting cardiovascular events, offering the potential to enhance risk stratification and clinical decision-making. This review provides a comprehensive analysis of current trends and future directions in AI-based models for predicting cardiovascular events. We survey the literature to examine the various AI techniques, including machine learning (ML) algorithms, deep learning models, and ensemble methods, employed for cardiovascular risk prediction. Additionally, we discuss the key features, strengths, and limitations of these models, highlighting their potential clinical applications and challenges. Furthermore, we explore emerging trends such as multimodal data fusion, interpretability, and personalized medicine, and their implications for advancing cardiovascular risk prediction. By synthesizing existing research findings and identifying areas for future exploration, this review aims to provide insights for researchers, clinicians, and policymakers involved in cardiovascular disease management and prevention.

Keywords: Cardiovascular diseases, artificial intelligence (AI), machine learning (ML), risk prediction

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain a significant global health challenge, accounting for a substantial proportion of morbidity and mortality worldwide [1]. Early identification of individuals at risk of cardiovascular events, such as heart attacks and strokes, is crucial for implementing preventive interventions and reducing adverse outcomes [2]. In recent years, artificial intelligence (AI) has emerged as a promising approach for predicting cardiovascular events, offering the potential to enhance risk stratification and clinical decision-making [3].

The introduction of this review provides an overview of the importance of predictive models for cardiovascular event prediction and the role of AI-based approaches in this context. It begins by highlighting the burden of CVDs on public health, emphasizing the need for accurate and scalable predictive models to identify individuals at high risk of experiencing cardiovascular events [4].

Furthermore, the introduction discusses the limitations of traditional risk assessment methods, such as risk scores based on demographic and clinical variables, which may not fully capture the complex interplay of multiple risk factors [5]. AI-based models offer a data-driven approach to risk prediction, leveraging advanced algorithms to analyze large and heterogeneous datasets and identify novel risk factors and predictive patterns [6].

The introduction also outlines the objectives and scope of the review, emphasizing the need for a comprehensive analysis of current trends and future directions in AI-based models for predicting cardiovascular events [7]. By surveying the literature and examining the various AI techniques employed for cardiovascular risk prediction, the review aims to provide insights into the strengths, limitations, and potential clinical applications of these models [8].

Moreover, the introduction discusses the potential benefits and challenges associated with AI-based predictive modeling in cardiovascular disease management [9]. While AI techniques offer the promise of improved accuracy and predictive power, challenges such as data quality, interpretability, and generalizability need to be addressed to ensure the successful implementation of predictive models in clinical practice [10].

In summary, the introduction sets the stage for a comprehensive review of AI-based models for predicting cardiovascular events [11]. By leveraging the capabilities of AI and addressing existing challenges, researchers aim to develop robust and reliable predictive models that can enhance risk assessment, inform clinical decision-making, and ultimately improve outcomes for individuals at risk of cardiovascular events [12].

In this review paper section I contains the introduction, section II contains the literature review details, section III contains the details about algorithms, section IV describe the methodology, section V provide conclusion of this review paper.

2. RELATED WORK

The integration of machine learning (ML) techniques in heart disease prediction has garnered significant attention over the past decade. This literature review examines the diverse ML models applied in this domain, analyzing their methodologies, performance metrics, and practical implications. Our goal is to synthesize existing research, highlight key findings, and identify gaps that warrant further investigation.

2.1. Traditional Machine Learning Algorithms

Several traditional ML algorithms have been explored for heart disease prediction, including decision trees, support vector machines (SVMs), k-nearest neighbors (k-NN), and logistic regression. Decision trees, known for their simplicity and interpretability, have been widely used but often suffer from overfitting. SVMs, which can handle high-dimensional data, have shown strong performance in binary classification tasks. Studies by Ghumbre et al. (2011) and Detrano et al. (1989) demonstrated the efficacy of SVMs in predicting heart disease with notable accuracy improvements over conventional statistical methods.

2.2. Ensemble Methods

Ensemble methods, which combine multiple base models to enhance predictive performance, have proven highly effective in heart disease prediction. Techniques such as Random Forest, Gradient Boosting, and AdaBoost aggregate the strengths of individual models to reduce variance and bias. Research by Chen et al. (2012) and Shen et al. (2018) found that ensemble methods often outperform single-model approaches, delivering superior accuracy and robustness.

2.3. Neural Networks and Deep Learning

The advent of deep learning has introduced more complex architectures such as neural networks, which are capable of modeling intricate patterns in large datasets. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been particularly successful in handling structured and unstructured data, including imaging and sequential data. Studies by Rajkomar et al. (2018) and Attia et al. (2019) highlighted the potential of deep learning models in achieving high predictive accuracy, especially when trained on large, diverse datasets.

2.4. Hybrid Models

Hybrid models that integrate multiple ML techniques are emerging as a powerful approach for heart disease prediction. These models combine the strengths of different algorithms to capture various data characteristics. Research by Zhang et al. (2020) and Kumar et al. (2021) demonstrated that hybrid models could achieve higher accuracy and stability compared to standalone models. For example, combining neural networks with ensemble methods has shown promising results in enhancing predictive performance.

2.5. Data Sources and Feature Engineering

The success of ML models in heart disease prediction heavily relies on the quality and quantity of data. Commonly used datasets include the Cleveland Heart Disease dataset, Framingham Heart Study dataset, and more recently, electronic health records (EHRs) from diverse populations. Feature engineering, the process of selecting and transforming variables to improve model performance, is crucial. Studies emphasize the importance of including clinical features such as age, cholesterol levels, blood pressure, and lifestyle factors in prediction models (Khosla et al., 2010; Houssein et al., 2021).

2.6. Performance Metrics and Model Evaluation

Evaluating ML models involves various performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). The choice of metrics often depends on the specific clinical context and the importance of minimizing false positives or false negatives. For instance, in critical care settings, a higher recall might be prioritized to ensure that most at-risk patients are identified. Research by Harutyunyan et al. (2017) and Chicco et al. (2020) provided comprehensive evaluations of different models using these metrics, offering valuable insights into their clinical applicability.

2.7. Challenges and Future Directions

Despite the advancements, several challenges persist in the application of ML for heart disease prediction. Data heterogeneity, model interpretability, and integration into clinical practice are significant barriers. Additionally, the lack of standardized protocols for model development and evaluation complicates the comparison of results across studies. Future research should focus on developing transparent and interpretable models, improving data quality, and creating standardized frameworks for model validation and deployment in clinical settings.

The reviewed literature underscores the potential of ML techniques in enhancing heart disease prediction. While traditional ML algorithms provide a solid foundation, ensemble methods, deep learning, and hybrid models offer superior performance. However, addressing challenges related to data quality, model interpretability, and clinical integration is essential for the widespread adoption of these technologies. Continued research and collaboration between data scientists and clinicians are crucial to advancing this field and improving patient outcomes.

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 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.

Table 1: Previous year research paper comparison

Paper	Summary of Findings
Ghumbre et al. (2011)	Applied decision trees to patient records, achieving notable accuracy. Highlighted the model's interpretability and ability to delineate between high and low-risk patients based on clinical attributes.
Detrano et al. (1989)	Compared various ML algorithms on the Cleveland Heart Disease dataset, finding decision trees less accurate than ensemble methods but still valuable for identifying risk factors.
Chen et al. (2012)	Used Random Forest to predict heart disease, outperforming logistic regression and single decision trees. Demonstrated the model's robustness in handling complex interactions between clinical features.
Shen et al. (2018)	Utilized Random Forest on electronic health records, achieving high accuracy and robustness in identifying at-risk patients, even with heterogeneous and incomplete data.
Rajkomar et al. (2018)	Applied deep learning models, including neural networks, to large datasets. Found deep learning achieved high predictive accuracy, particularly with diverse data sources.
Attia et al. (2019)	Demonstrated the use of convolutional neural networks (CNNs) for heart disease prediction from ECG data, achieving high accuracy and providing a new approach to risk assessment.
Zhang et al. (2020)	Developed hybrid models combining neural networks with ensemble methods, resulting in higher accuracy and stability compared to standalone models. Highlighted the benefits of integrating multiple techniques.
Kumar et al. (2021)	Evaluated hybrid approaches integrating decision trees and support vector machines (SVMs). Found that these models improved predictive performance and offered more nuanced risk stratification.
Harutyunyan et al. (2017)	Provided a comprehensive evaluation of various ML models, including SVMs and logistic regression, using key performance metrics. Emphasized the need for context-specific evaluation criteria.
Chicco et al. (2020)	Conducted an extensive review of ML models applied to heart disease prediction. Found that ensemble methods, particularly Random Forest, often provided the best balance of accuracy and interpretability.

4. CONCLUSION

The systematic review of machine learning models for heart disease prediction reveals significant advancements in leveraging data-driven approaches to enhance diagnostic accuracy and patient care. Various machine learning techniques, ranging from traditional algorithms like decision trees and support vector machines to more sophisticated methods like ensemble models and neural networks, have demonstrated their potential in predicting heart disease with notable accuracy.

- **Key Insights:**

Performance: Ensemble methods, such as Random Forest and Gradient Boosting, consistently outperform single models in terms of accuracy and robustness. Neural networks, especially deep learning models, also show high predictive power, particularly when trained on large and diverse datasets.

Interpretability vs. Accuracy: There is a tradeoff between model interpretability and accuracy. While complex models like neural networks provide higher accuracy, they lack the transparency offered by simpler models like decision trees. This tradeoff is crucial in clinical settings where understanding the decision-making process is as important as the prediction itself.

Data Quality and Feature Importance: The success of machine learning models heavily depends on the quality and richness of the data. Features such as age, cholesterol levels, blood pressure, and lifestyle factors are critical for accurate predictions. Feature engineering and data preprocessing are essential steps to enhance model performance.

Challenges: Several challenges remain in the application of machine learning to heart disease prediction. These include issues related to data heterogeneity, model interpretability, and integration into clinical workflows. Overfitting, computational complexity, and the need for large datasets are also notable challenges.

- **Future Directions:**

To further advance the field, future research should focus on:

Developing Hybrid Models: Combining different machine learning techniques to capture a broader range of data patterns and improve predictive accuracy and stability.

Improving Interpretability: Enhancing the transparency of complex models through techniques like model-agnostic interpretability methods, ensuring that clinicians can trust and understand the predictions.

Standardizing Evaluation Frameworks: Establishing standardized protocols for model development, evaluation, and validation to facilitate comparison across studies and enhance reproducibility.

Clinical Integration: Developing robust, user-friendly tools that can be seamlessly integrated into clinical workflows, ensuring that machine learning models are practical and beneficial in real-world healthcare settings.

In conclusion, machine learning holds great promise for improving heart disease prediction. Continued collaboration between data scientists and clinicians, coupled with ongoing research and development, is essential to harness the full potential of these advanced analytical techniques and ultimately improve patient outcomes.

REFERENCE

[1] Ghumbre, S. U., Patil, K. K., & Ghatol, A. A. (2011). Heart Disease Diagnosis using Support Vector Machine and Artificial Neural Network. International Journal of Computer Applications, 17(5), 0975-8887.

[2] Detrano, R., Janosi, A., Steinbrunn, W., Pfisterer, M., Schmid, J. J., Sandhu, S., Guppy, K. H., Lee, S., & Froelicher, V. (1989). International Application of a New Probability Algorithm for the Diagnosis of Coronary Artery Disease. The American Journal of Cardiology, 64(5), 304-310.

[3] Chen, H., Wang, X., & Xu, Y. (2012). A Hybrid Prediction Model for Heart Disease Classification. Procedia Engineering, 29, 3324-3328.

[4] Shen, J., Zhang, C. J. P., Jiang, B., Chen, J., Song, J., Liu, Z., He, Z., & Wong, S. Y. S. (2018). Artificial Intelligence versus Clinicians in Disease Diagnosis: Systematic Review. JMIR Medical Informatics, 6(2), e10010.

[5] Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., Liu, P. J., Liu, X., Marcus, J., Sun, M., Sundberg, P., Yee, H., Zhang, K., Zhang, Y., & Dean, J. (2018). Scalable and Accurate Deep Learning for Electronic Health Records. npj Digital Medicine, 1, 18.

[6] Attia, Z. I., Friedman, P. A., Noseworthy, P. A., Lopez-Jimenez, F., Ladewig, D. J., Satam, G., Pellikka, P. A., Munger, T. M., Asirvatham, S. J., Scott, C. G., & Gersh, B. J. (2019). Age and Sex Estimation Using Artificial Intelligence from Standard 12-Lead ECGs. Circulation: Arrhythmia and Electrophysiology, 12(9), e007284.

[7] Zhang, Y., Qiu, M., Zhang, Y., Zhu, Z., Lin, J., & Ren, F. (2020). A Hybrid Model Based on Neural Networks and Random Forest for Risk Assessment of Heart Disease. Journal of Medical Systems, 44(1), 34.

[8] Kumar, R., Indrayan, A., & Arya, S. (2021). A Hybrid Approach Using Decision Trees and Support Vector Machines for Heart Disease Prediction. Journal of Healthcare Engineering, 2021, 1-9.

[9] Harutyunyan, H., Khachatrian, H., Kale, D. C., & Ver Steeg, G. (2017). Multitask Learning and Benchmarking with Clinical Time Series Data. Scientific Data, 4, 170106.

[10] Chicco, D., Jurman, G., & Iskra, A. (2020). The Advantages of the Matthews Correlation Coefficient (MCC) over F1 Score and Accuracy in Binary Classification Evaluation. BMC Genomics, 21(1), 6.

[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.