Vol 6 No 1 (2024) *e*-ISSN: 2682-8383

Journal of Engineering Technology and Applied Physics

Real-Time Heart Rate Classification: Advancements and Challenges

Loo Chze Xin, Sumendra Yogarayan* and Siti Fatimah Abdul Razak
Faculty of Information Science and Technology, Multimedia University, Jalan Ayer Keroh Lama, 75450 Melaka, Malaysia.
**Corresponding author:* sumendra@mmu.edu.my, *ORCiD*: 0000-0002-5151-2300
https://doi.org/10.33093/jetap.2024.6.1.6
Manuscript Received: 21 July 2023, Accepted: 30 August 2023, Published: 15 March 2024

***Abstract* — This study focuses on the classification of heart rate, a condition with significant implications for health. The challenge lies in selecting an appropriate algorithm that can handle various types and severities of arrhythmia, enabling informed decisions and effective management. Factors such as accuracy, scalability, and efficiency are crucial for individuals without medical expertise. The selected algorithm should provide reliable classifications across different levels of severity, allowing individuals to monitor their heart rates in real-time and seek medical attention when needed. By addressing these challenges, this research aims to contribute to early diagnosis, treatment, and improved management of heart rate arrhythmia.**

Keywords—Heart rate, Detection, Prediction, Machine learning, IoT

I. INTRODUCTION

Heart disease is a prevalent health issue in today's generation, with ischemic heart disease being the leading cause of death. Accurate detection of heart rate arrhythmia plays a vital role in early diagnosis, treatment, and management of the condition. However, accurately classifying arrhythmia presents a challenge for individuals without medical expertise. To overcome this challenge, researchers have explored various approaches and technologies. For instance, Ambrosanio *et al.* [1] propose a multi-channel ultrasound system for non-contact heart rate monitoring, enabling convenient and accurate detection. Another study by Ru *et al.* [2] focuses on a human health monitoring system based on the Internet of Things (IoT), providing continuous monitoring and analysis of vital signs. In the context of specific applications, Huang *et al.* [3] introduce a heart rate monitoring framework using remote photoplethysmography for real-world drivers, offering a non-intrusive method for monitoring heart rate in a driving environment. Hussein *et al.* [4] present an automated remote cloud-based system for heart rate variability monitoring, enabling continuous monitoring and analysis of heart rate patterns. Other studies explore specific applications such as fall detection and heart rate monitoring for senior citizens, heart rate monitoring based on millimeter wave radar, and robust heart rate monitoring using wearable sensors. These studies showcase the diversity of approaches and technologies being investigated to accurately monitor and classify heart rate arrhythmia. A detailed study is presented in this paper to discuss all these approaches in order to do the comparison or review of all the techniques. A lot of work has been done by various researchers to design such kind of system using sensors, and different algorithms to detect and predict the heart rate arrhythmia.

II. RELATED WORKS

Following a quick overview of the several heart rate monitoring system methodologies, the approaches may be divided into two categories: detection and prediction. This section discusses each of these approaches along with its pros, and cons. The information about these approaches based on detecting component is shown in Table I. The following provides a thorough analysis of various approaches along with the pros and cons of some of the most popular solution.

A. Detection

Ru *et al.* [2] designed a comprehensive health monitoring system to collect real-time data on various health parameters and provide personalized feedback. This system enhances healthcare management accuracy and efficiency. However, challenges in technology, infrastructure, data security, and privacy may arise, while data visualization effectiveness could be compromised. Huang *et al.* [3] focused on developing a novel real-world driver heart rate monitoring system using remote photoplethysmography (PPG). This technology allows real-time, non-invasive heart rate monitoring to enhance driver safety. However, the accuracy of heart rate readings might be affected by environmental factors, noise, and movement during driving, requiring sophisticated setup.

Ambrosanio *et al.* [1] introduced a multi-channel ultrasound system for non-contact heart rate monitoring, offering a convenient approach without wearable devices. Continuous remote heart rate monitoring is possible in various settings, although challenges like specialized tools, noise interference, and sensitivity to subject movements may impact precision. Hussein *et al.* [4] presented a cloud-based system for remote heart rate variability monitoring, aiding early detection of cardiovascular issues. This system relies on cloud infrastructure and internet connectivity, which can limit user accessibility. Data security and reliability concerns also need to be addressed.

Beach *et al.* [5] designed a wrist-worn IoT-connected ECG monitor for continuous monitoring, offering convenience and individualized healthcare. However, technical expertise is necessary for implementation, and accuracy compared to medical-grade ECG devices might be reduced. Wang and Gao [6] explored real-time heart rate monitoring using wearable T-shirts in sports, employing machine learning algorithms. While their RBFN-LMPN model shows promise, challenges in measurement precision, reliability of wearable devices, and data privacy issues need to be addressed.

Chang [7] investigated heart rate acceleration motion sensor fusion in competitive sports using fast Fourier transform. Their proposed algorithm excels in quiet and dynamic motion but lacks advantages in sports with random characteristics. The focus on specific sports like basketball may limit its broader applicability. Bai [8] developed an IoT-based exercise parameter health monitoring platform using Adaptive Hybrid Filtering Algorithm. While the platform shows potential for accurate measurement, limitations like wireless network transmission environment and technical capacity need to be considered.

Li *et al.* [9] proposed an ethyl alpha-cyanoacrylate based fiber Fabry-Perot sensor for real-time heart rate monitoring across different body positions. The technology's scalability and practical implementation pose challenges that need further exploration. Sarowar *et al.* [10] designed an IoT-based fall detection and heart rate monitoring system for senior citizens. The system successfully detects daily activities of seniors but has a specific focus, limiting its broader applications.

Ling *et al.* [11] developed a non-contact heart rate monitoring system using millimeter wave radar technology. While accurate results are achieved across scenarios, limitations in single-person monitoring and potential lack of finely filtered heartbeat data need to be addressed. Bai, Huang & Liu [12] proposed a real-time non-contact heart rate monitoring system using a camera with CNN and LiPPG. The system captures high accuracy even in low light, but issues in dark environments may limit its effectiveness.

Zhao and Liu [13] introduced an exercise load monitoring system based on IoT with an Adaptive Hybrid Filtering algorithm. While higher iteration numbers improve preprocessing performance, signal processing remains influenced by the number of iterations. Han [14] utilized adaptive wireless transmission for target heart rate monitoring in sports using wearable sensors and Kalman filtering. The approach maintains stable output but requires careful calibration and synchronization of wearable devices while facing potential communication range and interference challenges. Badr *et al.* [15] proposed an artificial neural network-based approach for detecting heart arrhythmia using ECG data and Pan-Tompkins algorithm. Despite the promising genetic algorithm-enhanced classification accuracy, a larger and more diverse dataset for training is needed for improved results.

Table I: Heart rate monitoring detection.

No	Authors	Year	Pros	Cons
1	Hussein *et al.*	2018	Remote monitoring of heart rate variability, early cardiovascular issue detection.	User accessibility limitations, dependence on cloud infrastructure, data security and connectivity challenges.
2	Bai, Huang & Liu	2018	High accuracy under low illumination conditions.	Ineffective in dark environments.
3	Beach *et al.*	2018	Convenient wrist-worn continuous monitoring, individualized healthcare.	Requires technical expertise, reduced accuracy compared to medical-grade ECG devices, improved noise performance.
4	Ambrosanio *et al.*	2020	Continuous and remote heart rate monitoring without wearable devices or touch.	Requires specialized tools, noise and interference affect precision, not robust to subject movements and artifacts.
5	Ru *et al.*	2021	Improved healthcare management accuracy and efficiency.	Technological, infrastructural, data security and privacy issues, ineffective data visualization.
6	Wang & Gao	2021	Development of RBFN-LMPN model with reduced error.	Wearable device measurement precision, data privacy issues, limited to volleyball focus.
7	Huang, Wu & Wu	2021	Real-time, non-invasive heart rate monitoring for drivers, enhancing safety.	Requires sophisticated technology setup, accuracy affected by environment, noise, and movement during driving.
8	Chang	2021	Accurate algorithm for quiet and dynamic motion detection, basketball focus.	Less effective in competitive sports with random characteristics, limited applicability to other sports.

No	Authors	Year	Pros	Cons
9	Li *et al.*	2021	Real-time heart rate monitoring on various body positions.	Scalability limitations, challenges in practical implementation.
10	Han	2021	Maintained stable output, suitable for sports target heart rate monitoring.	Requires proper calibration, synchronization of wearable sensors, wireless communication issues.
11	Ling *et al.*	2022	Accurate results in different scenarios, improved accuracy.	Limited to single-person monitoring, insufficiently fine heartbeat filtering.
12	Sarowar *et al.*	2022	Successful ADL detection without false positives, tailored for senior citizens.	Focus solely on senior citizens, limited scope.
13	Zhao & Liu	2022	Improved preprocessing performance with higher iteration numbers.	Preprocessing performance affected by iteration numbers.
14	Bai	2022	Higher average standard deviation for measured values, improved accuracy.	Limited by wireless network, technical capabilities, terminal size, processing, and battery capacity.
15	Badr *et al.*	2022	Pan-Tompkins recommended, genetic algorithm improves classification accuracy.	Need for larger and diverse training dataset.

B. *Prediction*

Heart rate classification prediction and heart disease prediction can be related in several ways. Heart rate is a physiological measurement that can be used to assess a person's overall health and well-being. Changes in heart rate can be indicative of a number of underlying health conditions, including heart disease. For example, a consistently high heart rate can be a sign of hypertension, while a consistently low heart rate can be a sign of bradycardia. Both hypertension and bradycardia are risk factors for heart disease. A number of machine learning algorithm is being discussed as shown in Table II. Following a thorough analysis of the research literature, it is possible to classify the methods used to identify and predict heart rate into distinct subcategories.

Ahmad and Polat [16] proposed the use of machine learning model to predict heart disease. The authors explored using Jellyfish optimization algorithm with Cleveland Heart Disease dataset. The Jellyfish algorithm is a swarm-based metaheuristic algorithm that can be used with machine learning methods to optimize hyperparameters. The Jellyfish optimization algorithm and support vector machine (SVM) classifier achieved the highest performance, with an accuracy of 98.47%. The other algorithms evaluated were artificial neural networks (ANN) (98.21%), decision tree (DT) (98.09%), and AdaBoost (97.96%).

Pramukantoro and Gofuku [17] examined on heartbeat classifier based on RR interval for real-time and continuous heartbeat monitoring. The authors used six machine learning algorithms that are LR, NN, SVM, ANN, DT and RF with MIT-BIH arrhythmia dataset. The RF algorithm outperformed the other methods with an impressive accuracy of 99.67%. In contrast, the SVM demonstrated an accuracy of 92.57%, while the NN achieved 92.50%. The RF model achieved a score of 96.22%, the ANN reached 96.35%, and the DT performed remarkably well with an accuracy of 99.31%.

Sarra *et al.* [18] introduced a machine learning model with the potential to improve the accuracy of diagnosing and predicting heart disease while also reducing computational loads. The researchers utilized the SVM algorithm as their classification model. The findings revealed that when applied to the Cleveland Heart Disease dataset the SVM algorithm achieved an accuracy rate of 89.47%. Similarly, on the Statlog dataset it reached an accuracy rate of 89.7%. These results indicate that the SVM algorithm effectively enhanced the accuracy by 5.26% and 4.41% respectively.

Motarwar *et al.* [19] explored the application of machine learning methods in predicting the likelihood of heart disease. The researchers used algorithms, like RF, SVM, gaussian naïve bayes (NB), Hoeffding decision tree (HT) and logistic model tree (LMT). The authors evaluated the performance using the Cleveland Heart Disease dataset. The findings show that the RF algorithm achieved an accuracy rate of 95.08%. NB followed closely with an accuracy of 92.44% while SVM had an accuracy rate of 90.16%. HT and LMT had accuracies with HT achieving 81.24% and LMT achieving 80.69% respectively.

Jindal *et al.* [20] presented a system to predict heart disease using machine learning techniques. The authors utilized the Cleveland Heart Disease dataset for this research. The authors used three machine learning models, including LR, k Nearest Neighbours (KNN) and random forest (RF) classifier. The accuracy of their model was found to be 87.5% surpassing the accuracy achieved by models, which stood at 85%.

Sharma *et al.* [21] explored on different machine learning techniques to predict heart disease and determine the algorithm that performed the best. The authors utilized the Cleveland Heart Disease dataset, which is accessible, through the UCI machine learning repository. Four machine learning algorithms, RF, SVM, DT and LR were employed in the investigation. Notably the RF algorithm exhibited an accuracy rate of 99% followed by SVM with 93% accuracy. On the hand the DT algorithm had an accuracy of 85% while LR achieved an accuracy of 88%.

Princy *et al.* [22] focused on supervised machine learning algorithms for predicting cardiac disease. The authors used six classification model: DF, NB, LR, RF, SVM and KNN. The algorithms were evaluated on the Cardiovascular Disease dataset. The authors found that the DT achieved a notable accuracy of 73%, LR achieved 72%, SVM achieved 72%, RF achieved 71%, NB achieved 60% and KNN achieved 66%. The authors found that the dimension of dataset plays a major role in the performance of algorithms, the reduction of dimension affects the capability of RF and KNN algorithms.

Ganesan and Sivakumar [23] explored on disease diagnosis model to monitor, predict, and diagnose heart disease. The study used Cleveland Heart Disease dataset and healthcare sensors to predict heart disease in patients. Four classification algorithms were used to classify the patient data that are J48, SVM, LR, and MLP. The study found that J48 classifier achieved the highest accuracy of 91.48%, followed by SVM (84.07%), LR (83.70%), and MLP (78.14%).

Bashir *et al.* [24] explored the use of data science to improve the accuracy of heart disease prediction. The study applied five machine learning algorithms: DT, LR, LR with SVM, NB, and RB with Cleveland Heart Disease dataset. The study found that the decision tree (DT) algorithm achieved an accuracy of 82.22%, the logistic regression (LR) algorithm achieved an accuracy of 82.56%, the logistic regression with support vector machine (SVM) algorithm achieved an accuracy of 84.85%, the naïve Bayes (NB) algorithm achieved an accuracy of 84.24%, and the random forest (RF) algorithm achieved an accuracy of 84.17%.

Haq *et al.* [25] proposed a hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms. The system was tested on the Cleveland Heart Disease dataset. There were seven well-known classifiers used that are LR, KNN, artificial neural networks (ANN), support vector machine (SVM), naïve bayes (NB), decision tree (DT), and RF. Additionally, three feature selection algorithms that were used that are Relief, minimum redundancy maximum relevance (mRMR), and least absolute shrinkage and selection operator (LASSO). The logistic regression classifier with the Relief feature selection algorithm showed the best performance in terms of accuracy of 89% as compared to the rest.

Khourdifi and Bahaj [26] presented on heart disease prediction and classification using machine learning algorithms. The authors explored on the Fast Correlation-Based Feature Selection (FCBF), method to filter redundant features in order to improve the quality of heart disease classification. Besides, the authors also explored the results of the particle swarm optimization (PSO) optimization that are considered the initial values of the ant colony optimization (ACO). The authors used Cleveland Clinic Foundation dataset for the purpose of this study. There were five classification algorithm used that are KNN, SVM, NB, RF and Multilayer Perception (MLP). The proposed optimized model by FCBF, PSO and ACO achieve an accuracy score of 99.65% with KNN, 99.6% with RF, 91.65% with MLP, 86.15% with NB and 83.55% with SVM.

Nassif *et al.* [27] focused on the use of machine learning for the accurate classification of patients with coronary artery disease (CAD). The authors examined three machine learning algorithms: SVM, NB and KNN. The study used the Cleveland Heart Disease dataset for this purpose of study. The study found that the NB achieved the highest accuracy of 84%, followed by SVM with 83% accuracy and KNN with 80% accuracy.

Table II: Heart rate monitoring prediction.

Author	Year	Dataset	Algorithms	Accuracy
Ahmad and Polat	2023	Cleveland Heart Disease	Jellyfish optimization algorithm + SVM, ANN, DT, AdaBoost	SVM (98.47%), ANN (98.21%), DT (98.09%), AdaBoost (97.96%)
Pramukantoro and Gofuku	2022	MIT-BIH arrhythmia dataset	LR, NN, SVM, ANN, DT, RF	RF (99.67%), SVM (92.57%), NN (92.50%), ANN (96.35%), DT (99.31%)
Sarra *et al.*	2022	Cleveland Heart Disease, Statlog	SVM	SVM (89.47%) and SVM (89.7%)
Motawar *et al.*	2020	Cleveland Heart Disease	RF, Gaussian NB, SVM, Hoeffding Decision Tree, LMT	RF (95.08%), Gaussian NB (92.44%), SVM (90.16%), Hoeffding decision tree (81.24%), LMT (80.69%)
Jindal *et al.*	2020	Cleveland Heart Disease	LR, KNN, RF	RF (87.5%), KNN and LR (Not Mentioned)
Sharma *et al.*	2020	Cleveland Heart Disease	RF, SVM, DT, LR	RF (99%), SVM (93%), DT (85%), LR (88%)
Princy *et al.*	2020	Cardiovascular Disease	DF, NB, LR, RF, SVM, KNN	DT (73%), LR (72%), SVM (72%), RF (71%), NB (60%), KNN (66%)
Ganesan and Sivakumar	2019	Cleveland Heart Disease	J48, SVM, LR, MLP	J48 (91.48%), SVM (84.07%), LR (83.70%), MLP (78.14%)
Bashir *et al.*	2019	Cleveland Heart Disease	DT, LR, LR with SVM, NB, RB	DT (82.22%), LR (82.56%), LR with SVM (84.85%), NB (84.24%), RF (84.17%)
Haq *et al.*	2018	Cleveland Heart Disease	LR, KNN, ANN, SVM, NB, DT, RF	LR (89%), KNN (99.65%), SVM (83.55%), ANN (91.65%), DT (86.15%), RF (99.6%)

Author	Year	Dataset	Algorithms	Accuracy
Khouridfi and Bahaj	2018	Cleveland Clinic Foundation	KNN, SVM, NB, RF, MLP	KNN (99.65%), RF (99.6%), MLP (91.65%), NB (86.15%), SVM (83.55%)
Nassif *et al.*	2018	Cleveland Heart Disease	SVM, NB, KNN	NB (84%), SVM (83%), KNN (80%)

III. ADVANCEMENT AND CHALLENGES

In recent times, the integration of detection and prediction monitoring systems has become essential in modern healthcare and wellness strategies. These systems bring a multitude of advantages, but also challenges that deserve consideration. The advancements achieved by these systems have fundamentally transformed our approach to health management, enabling timely interventions and informed decisions. Specifically, detection systems geared towards heart rate and arrhythmia monitoring offer early anomaly identification, a critical aspect that empowers healthcare professionals to address potential cardiovascular issues proactively. The integration of machine learning has significantly strengthened these systems' accuracy, enhancing their ability to determine complex patterns within health data that may dodge human perception.

Furthermore, the progression of prediction monitoring systems represents an evolution beyond immediate identification, delving into forecasting future health trends. These systems leverage historical health data and predictive algorithms to enable individuals and healthcare providers to anticipate potential health risks. This advancement provides the means for individuals to make informed lifestyle choices and healthcare decisions, fostering personalized and effective health management strategies.

However, along with these advancements come a set of challenges that deserve attention. Technological limitations, particularly the requirement for advanced sensors and infrastructure, can delay accessibility, especially in resource-constrained regions. The dependence on cloud-based solutions and internet connectivity introduces the potential for disruptions in data transmission, amplifying concerns regarding data security and privacy. Given the sensitive nature of the health data collected and analyzed, ensuring robust encryption and adherence to data protection regulations becomes vital.

Another challenge revolves around interpreting the data generated by these systems. False positives and negatives can occur, potentially leading to unnecessary medical interventions or the oversight of critical health issues. Additionally, while machine learning improves accuracy, the opacity of certain algorithms may complicate the comprehension of specific predictions, potentially wear down user trust and acceptance.

IV. CONCLUSION

IoT-enabled heart rate monitoring has revolutionized healthcare and personal well-being, allowing individuals to monitor and manage their cardiovascular health effectively. The advancements highlighted in the reviewed articles emphasize the benefits of real-time, continuous, and remote heart rate monitoring through wearable devices equipped with sensors and connectivity features. This technology empowers users to make informed decisions about their physical activities, stress levels, and overall health, leading to improved self-awareness and early detection of potential health issues. However, there are still research gaps to be addressed. Future investigations should focus on integrating heart rate monitoring with other health parameters and contextual data, such as sleep patterns, activity levels, and environmental factors, to provide a comprehensive view of an individual's health status and enable personalized interventions. Additionally, the validation and standardization of non-contact heart rate monitoring techniques need attention to ensure accuracy and reliability across different settings and populations, expanding the reach of monitoring solutions. Furthermore, addressing the security and privacy aspects of IoT-enabled heart rate monitoring systems is crucial to protect sensitive health data through robust security measures and transparent privacy frameworks. By addressing these research gaps, the full potential of IoT-enabled heart rate monitoring can be harnessed, resulting in improved well-being, proactive healthcare management, and a transformative impact on the healthcare landscape.

ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their constructive and invaluable feedback.

REFERENCES

[1] M. Ambrosanio, S. Franceschini, G. Grassini and F. Baselice, "A Multi-Channel Ultrasound System for Non-Contact Heart Rate Monitoring," *IEEE Sensors J.*, vol. 20, no. 4, pp. 2064–2074, 2020.

[2] L. Ru, B. Zhang, J. Duan, G. Ru, A. Sharma, G. Dhiman, G. S. Gaba, E. S. Jaha and M. Masud, "A Detailed Research on Human Health Monitoring System Based on Internet of Things," *Wireless Comm. and Mobile Comput.*, vol. 2021, no. 5592454, 2021.

[3] P. W. Huang, B. J. Wu and B. F. Wu, "A Heart Rate Monitoring Framework for Real-World Drivers Using Remote Photoplethysmography," *IEEE J. Biomed. and Health Informa.*, vol. 25, no. 5, pp. 1397–1408, 2021.

[4] A. F. Hussein, N. A. Kumar, M. Burbano-Fernandez, G. Ramirez-Gonzalez, E. Abdulhay and V. H. C. de Albuquerque, "An Automated Remote Cloud-Based Heart Rate Variability Monitoring System," *IEEE Access*, vol. 6, pp. 77055–77064, 2018.

[5] C. Beach, S. Krachunov, J. Pope, X. Fafoutis, R. J. Piechocki, I. Craddock and A. J. Casson, "An Ultra Low Power Personalizable Wrist Worn ECG Monitor Integrated with IoT Infrastructure," *IEEE Access*, vol. 6, pp. 44010–44021, 2018.

[6] Z. Wang and Z. Gao, "Analysis of Real-Time Heartbeat Monitoring Using Wearable Device Internet of Things System In Sports Environment," *Computat. Intellig.*, vol. 37, no. 3, pp. 1080–1097, 2021.
[7] B. Chang, "Application of Heart Rate Acceleration Motion Wireless Sensor Fusion in Individual Special Competitive Sports," *J. Sensors*, vol. 2021, no. 5723567, 2021.
[8] X. Bai, "Designing and Implementing a Terminal Platform to Manage and Detect the Health of Exercise Parameters Based on Internet Objects," *J. Sensors*, vol. 2022, no. 7121741, 2022.
[9] Y. Li, B. Dong, E. Chen, X. Wang and Y. Zhao, "Heart-Rate Monitoring with an Ethyl AlphaCyanoacrylate Based Fiber Fabry-Perot Sensor," *IEEE J. Select. Topics Quant. Electron.*, vol. 27, no. 4, pp. 5600206, 2021.
[10] M. H. Sarowar, M. F. K. Khondakar, H. S. Roy, H. Ullah, R. Ahmed and Q. D. Hossain, Q. D. "Internet of Things Based Fall Detection and Heart Rate Monitoring System for Senior Citizens," *Int. J. Electr. and Comput. Eng.*, vol. 12, no. 3, pp. 3204–3216, 2022.
[11] Z. Ling, W. Zhou, Y. Ren, J. Wang and L. Guo, "Non-Contact Heart Rate Monitoring Based on Millimeter Wave Radar," *IEEE Access*, vol. 10, pp. 74033–74044, 2022.
[12] G. Bai, J. Huang and H. Liu, "Real-Time Robust Noncontact Heart Rate Monitoring with A Camera," *IEEE Access*, vol. 6, pp. 33682–33691, 2018.
[13] K. T. Zhao and W. J. Liu, "The Design of the Exercise Load Monitoring System Based on Internet of Things," *Wireless Comm. and Mobile Comput.*, vol. 2022, no. 8011124, 2022.
[14] Z. Han, "Using Adaptive Wireless Transmission of Wearable Sensor Device for Target Heart Rate Monitoring of Sports Information," *IEEE Sensors J.*, vol. 21, no. 22, pp. 25027–25034, 2021.
[15] M. Badr, S. Al-Otaibi, N. Alturki and T. Abir, "Detection of Heart Arrhythmia on Electrocardiogram using Artificial Neural Networks," *Computat. Intellig. and Neurosci.*, vol. 2022, no. 1094830, 2022.
[16] A. A. Ahmad and H. Polat, "Prediction of Heart Disease Based on Machine Learning Using Jellyfish Optimization Algorithm," *Diagnostics*, vol. 13, no. 14, pp. 2392, 2023.
[17] E. S. Pramukantoro and A. Gofuku, "A Heartbeat Classifier for Continuous Prediction using A Wearable Device," *Sensors*, vol. 22, no. 14, pp. 5080, 2022.
[18] R. R. Sarra, A. M. Dinar, M. A. Mohammed and K. H. Abdulkareem, "Enhanced Heart Disease Prediction Based on Machine Learning and $\chi 2$ Statistical Optimal Feature Selection Model," *Designs*, vol. 6, no. 5, pp. 87, 2022.
[19] P. Motarwar, A. Duraphe, G. Suganya and M. Premalatha, "Cognitive Approach for Heart Disease Prediction using Machine Learning," in *2020 IEEE Int. Conf. Emerg. Trends Inform. Technol. and Eng.*, pp. 1-5, 2020.
[20] H. Jindal, S. Agrawal, R. Khera, R. Jain and P. Nagrath, "Heart Disease Prediction using Machine Learning Algorithms," *IOP Conf. Series: Mater. Sci. and Eng.*, vol. 1022, no. 1, pp. 012072, 2021.
[21] V. Sharma, S. Yadav and M. Gupta, "Heart Disease Prediction using Machine Learning Techniques," in *2020 IEEE 2nd Int. Conf. Adv. Comput., Comm. Contr. and Netw.*, pp. 177-181, 2020.
[22] R. J. P. Princy, S. Parthasarathy, P. S. H. Jose, A. R. Lakshminarayanan and S. Jeganathan, "Prediction of Cardiac Disease using Supervised Machine Learning Algorithms," in *2020 IEEE 4th Int. Conf. Intellig. Comput. and Contr. Sys.*, pp. 570-575, 2020.
[23] M. Ganesan and N. Sivakumar, "IoT Based Heart Disease Prediction and Diagnosis Model for Healthcare using Machine Learning Models," in 2019 *IEEE Int. Conf. Sys., Comput., Auto. and Netw.*, pp. 1-5, 2019.
[24] S. Bashir, Z. S. Khan, F. H. Khan, A. Anjum and K. Bashir, "Improving Heart Disease Prediction using Feature Selection Approaches," in *2019 IEEE 16th Int. Bhurban Conf. Appl. Sci. and Technol.*, pp. 619-623, 2019.
[25] A. U. Haq, J. P. Li, M. H. Memon, S. Nazir and R. Sun, "A Hybrid Intelligent System Framework for The Prediction of Heart Disease Using Machine Learning Algorithms," *Mobile Inform. Sys*, vol. 2018, no. 3860146, 2018.
[26] Y. Khourdifi and M. Baha, "Heart Disease Prediction and Classification using Machine Learning Algorithms Optimized by Particle Swarm Optimization and Ant Colony Optimization," *Int. J. Intellig. Eng. & Sys.*, vol. 12, no. 1, pp. 242-252, 2019.
[27] A. B. Nassif, O. Mahdi, Q. Nasir, M. A. Talib and M. Azzeh, "Machine Learning Classifications of Coronary Artery Disease," in *2018 IEEE Int. Joint Sym. Artif. Intellig. and Nat. Language Process.*, pp. 1-6, 2018.