



A Review on Heart Disease Prediction Using Different Learning Techniques

Ahmed Yasar M T¹, Ameena Salim², Sahadiya Salam³, Sahal K S⁴ and Nasreen Ali A⁵

^{1,2,3,4}Research Scholars, ⁵Professor

Department of Computer Science, Ilahia College of engineering and technology Mulavoor, India

ABSTRACT

Heart failure is a chronic disease affecting millions worldwide. An efficient AI based technique is needed to predict heart failure based status early and take necessary actions to overcome this worldwide issue. This review paper comprehensively examines various research works and methodologies focused on Heart disease analysis, ecg selection, data assessment, life prediction. This survey paper systematically reviews and compares various machine learning techniques employed in the prediction of heart disease. Spanning a diverse array of methodologies, from traditional methods to state-of-the-art deep learning approaches, the paper aims to provide a comprehensive overview of the strengths, limitations, and comparative performance of each technique. By synthesizing findings from a multitude of studies, it offers valuable insights into the evolving landscape of heart disease prediction, shedding light on the potential advancements and challenges in this critical domain of healthcare.

Keywords: Heart failure, deep learning, disease prediction, ecg selection

1. INTRODUCTION

Heart disease remains a leading cause of mortality worldwide, prompting extensive research into predictive methodologies aimed at early detection and effective management. Heart disease describes a range of conditions that affect your heart. Today, cardiovascular diseases are the leading cause of death worldwide with 17.9 million deaths annually, as per the World Health Organization reports [1] In recent years, a plethora of studies have emerged, each proposing unique approaches to heart disease prediction. This survey paper seeks to provide a comprehensive overview and comparison of these diverse methodologies, shedding light on the advancements, challenges, and potential future directions in the field.

Early detection of cardiac diseases and continuous supervision of clinicians can reduce the mortality rate.[2] However, accurate detection of heart diseases in all cases and consultation of a patient for 24 hours by a doctor is not available since it requires more sapience, time and expertise. Heart disease is very fatal and it should not be taken lightly. Heart disease happens more in males than females, which can be read further from Harvard Health Publishing [3]. Researchers found that, throughout life, men were about twice as likely as women to have a heart attack.at higher risk persisted even after they accounted for traditional risk factors of heart disease, including high cholesterol, high blood pressure, diabetes, body mass index, and physical activity[4].The significance of accurate heart disease prediction cannot be overstated, as timely identification can significantly impact patient outcomes and healthcare resource allocation. With an increasing emphasis on leveraging advanced technologies such as machine learning, artificial intelligence, and data mining, the landscape of predictive models for heart disease has evolved rapidly. As a result, it is crucial to consolidate and compare the findings and methodologies from various studies to gain a holistic understanding of the state of the art in this domain.

This survey paper will systematically analyze and juxtapose different papers, focusing on aspects such as the types of data utilized, feature selection techniques, model architectures, performance metrics, and validation methodologies. By synthesizing and comparing these elements, we aim to provide readers with a comprehensive understanding of the strengths and limitations of existing predictive models for heart disease.

Moreover, this survey is intended to serve as a valuable resource for researchers, practitioners, and healthcare professionals who seek to navigate the myriad of approaches in heart disease prediction. By critically examining and synthesizing the findings from diverse studies, we endeavor to offer insights that can inform the development of more robust and accurate predictive models, ultimately contributing to improved patient care and outcomes.

In summary, this survey paper embarks on a journey to compare and contrast various papers related to heart disease prediction, aiming to offer a comprehensive understanding of the existing landscape while identifying potential avenues for future research and development in this critical domain of healthcare.

1.1 COMMON HEART DISEASES

Heart diseases encompass a wide array of conditions that affect the cardiovascular system. Coronary Artery Disease (CAD) arises from the buildup of plaque in the coronary arteries, potentially leading to chest pain or heart attacks. Heart Failure occurs when the heart cannot pump enough blood to meet the body's needs, while Arrhythmias manifest as irregular heartbeats, leading to palpitations or dizziness. Heart Valve Disease involves issues with the heart's valves, potentially causing symptoms like shortness of breath. According to the survey of the World Health Organization (WHO), 17.5 million total global deaths occur because of heart attacks and strokes. More than 75% of deaths from cardiovascular diseases occur mostly in middle-income and low-income countries. Also, 80% of the deaths that occur due to CVDs are because of stroke and heart attack [5]

Additionally, Cardiomyopathy refers to diseases of the heart muscle, potentially leading to reduced heart function. Peripheral Artery Disease (PAD) affects blood vessels outside the heart, often causing leg pain and reduced mobility. Congenital Heart Defects are structural problems present at birth, impacting the heart's chambers, valves, or blood vessels. Myocarditis signifies inflammation of the heart muscle, often due to viral infections, leading to symptoms such as chest pain and fatigue. Pericardial Disease encompasses conditions affecting the pericardium, the membrane around the heart.

Rheumatic Heart Disease results from untreated strep throat, leading to heart valve damage, while Aortic Aneurysms present as bulges in the body's main artery, potentially causing severe complications. Hypertrophic Cardiomyopathy involves genetic thickening of the heart muscle, while Mitral Valve Prolapse refers to improper closure of the valve between the heart's chambers. Heart Infections, such as endocarditis or myocarditis, can lead to serious complications.

These diverse conditions underline the complexity of heart diseases, emphasizing the need for a comprehensive understanding and management of each condition to ensure effective care and treatment. Heart block occurs when the electrical signals that control the heartbeat are delayed or interrupted as they move from the heart's upper chambers (atria) to the lower chambers (ventricles). This can result in an abnormally slow heart rate and lead to symptoms such as dizziness, fainting, fatigue, and shortness of breath.

There are different types of heart block, including first-degree, second-degree, and third-degree (complete) heart block, each with varying degrees of severity. Treatment for heart block may involve medications, implantation of a pacemaker, or other interventions depending on the type and severity of the block.

1.2 HEART DISEASE DETECTION METHODS USING DEEP LEARNING

Deep learning techniques for heart disease prediction involve the utilization of advanced neural network architectures to process and analyze medical data, enabling accurate predictions related to the likelihood of heart disease. These techniques are designed to automatically discern intricate patterns and features within medical data, surpassing the capabilities of traditional methods. Deep learning is the branch of machine learning that was named in 2006. It was inspired by the structure of the human brain, which contains neural networks. It is a data-processing method that uses a multiple-layer technique [6]. The working of the layers can be considered to be a layer receiving weighted input, transforming it into mostly nonlinear functions, and then sending the output to the next layer [7]

Convolutional Neural Networks (CNNs): CNNs are widely employed for the analysis of medical images, including MRI scans, CT scans, and X-rays. Due to their ability to learn spatial hierarchies of features within images, CNNs are adept at identifying subtle anomalies that may indicate the presence of heart disease.

Recurrent Neural Networks (RNNs): RNNs are particularly effective for processing sequential data, such as electrocardiogram (ECG) signals that represent the electrical activity of the heart over time. Leveraging their capacity to capture temporal dependencies in data, RNNs are well-suited for detecting irregular heart rhythms and other ECG abnormalities associated with heart disease.

Hybrid Models: In some instances, hybrid models integrate CNNs and RNNs to analyze multimodal medical data, incorporating information from diverse sources such as imaging, clinical records, and genetic data. This fusion of neural network architectures aims to leverage their complementary strengths, leading to a more comprehensive approach to heart disease prediction.

Transfer Learning: Deep learning models, originally trained on extensive datasets, can be adapted using transfer learning to analyze medical data for heart disease prediction. This process involves the utilization of pre-trained models, subsequently fine-tuned on medical data. By doing so, this approach effectively leverages knowledge gained from diverse sources, enhancing the accuracy of predictions.

Attention Mechanisms: Within deep learning models, attention mechanisms enable the identification of critical features within the input data, allowing the model to focus on relevant information for heart disease prediction. This enhances the interpretability and performance of the model, contributing to more accurate predictions.

In summary, deep learning techniques for heart disease prediction represent a state-of-the-art approach to uncovering complex patterns within medical data. By harnessing these advanced methodologies, the potential for more accurate and early detection of heart-related conditions is greatly enhanced.

1.3 HEART DISEASE DETECTION USING MACHINE LEARNING

Heart disease detection using machine learning involves the application of various algorithms to analyze medical data and make predictions related to the presence or likelihood of heart disease[8]. Here are some key approaches:

Supervised Learning Algorithms:

- a. Logistic Regression: This algorithm is commonly used for binary classification tasks, such as determining the presence or absence of heart disease based on various input features.
- b. Support Vector Machines (SVM): SVMs can effectively classify patients into different risk groups based on features derived from medical data, aiding in heart disease prediction.

Decision Trees and Random Forest:

Decision trees and ensemble methods like random forests are utilized to analyze patient data and identify important risk factors associated with heart disease. These methods can handle both numerical and categorical data, making them versatile for medical datasets.

Naive Bayes Classifier:

This probabilistic classifier is applied to assess the probability of a patient having heart disease based on input features. It assumes independence among features, making it particularly useful for medical data analysis.

Unsupervised Learning for Anomaly Detection:

Clustering algorithms, such as k-means or DBSCAN, can be employed to identify abnormal patterns in patient data, potentially indicating the presence of heart disease. Anomalies detected through unsupervised learning may prompt further examination by healthcare professionals.

Feature Selection and Dimensionality Reduction:

Techniques like Principal Component Analysis (PCA) and feature selection algorithms help in identifying the most relevant features from the data, aiding in the creation of more effective predictive models for heart disease detection.

Ensemble Learning:

Utilizing ensemble methods, such as boosting or bagging, can enhance the predictive performance of machine learning models for heart disease detection by combining the strengths of multiple models.

These machine learning techniques, when applied to medical data, contribute to the development of predictive models that assist in the early detection and assessment of heart disease, ultimately supporting healthcare professionals in making informed decisions for patient care.

1.4 SIGNIFICANCE OF LEARNING TECHNIQUES IN HEART DISEASE PREDICTION

The significance of learning techniques in heart disease prediction lies in their ability to leverage advanced algorithms to analyze complex medical data, leading to improved accuracy, early detection, and personalized risk assessment. Here are some key points highlighting their significance:

Early Detection: Learning techniques enable the identification of subtle patterns and risk factors within medical data, facilitating the early detection of heart disease, potentially allowing for timely intervention and treatment.

Personalized Risk Assessment: By analyzing diverse patient data, learning techniques can provide personalized risk assessments, considering individual differences, medical history, genetic factors, and lifestyle, leading to more tailored and targeted preventive strategies.

Enhanced Accuracy: Advanced learning techniques, such as deep learning and ensemble methods, contribute to higher accuracy in predicting heart disease by effectively capturing intricate patterns and interactions within complex medical datasets.

Integration of Multimodal Data: Learning techniques can integrate diverse types of medical data, including imaging, genetic information, clinical records, and lifestyle factors, enabling a more comprehensive assessment of heart disease risk.

Decision Support for Healthcare Professionals: By providing interpretable insights and risk assessments, learning techniques support healthcare professionals in making informed decisions, optimizing patient care, and prioritizing resources for at-risk individuals.

Public Health Impact: Accurate prediction and risk assessment of heart disease contribute to public health efforts by identifying high-risk populations, guiding preventive measures, and potentially reducing the overall burden of heart-related conditions.

Continuous Improvement: Learning techniques allow for continuous refinement and improvement of predictive models as more data becomes available, fostering ongoing advancements in heart disease prediction and management.

In summary, learning techniques play a pivotal role in revolutionizing heart disease prediction by enabling early detection, personalized risk assessment, enhanced accuracy, and informed decision-making, ultimately leading to improved patient outcomes and public health impact.

2. LITERATURE REVIEW

According to Azam Mehmood Qadri, Ali Raza, Kashif Munir and Mubarak S. Almutairi, "Effective Feature Engineering Technique for Heart Disease Prediction with Machine Learning" [9]. This research paper focuses on an efficient machine learning-based technique needed to predict heart failure health status early and take necessary actions to overcome this issue. They developed an approach to enhance heart failure detection based on patient health parameter data involving machine learning. This study helps improve heart failure detection at its early stages to save patients' lives. They employed nine machine learning-based algorithms for comparison and proposed a novel Principal Component Heart Failure (PCHF) feature engineering technique to select the most prominent features to enhance performance. PCHF mechanism is used by creating a new feature set as an innovation to achieve the highest accuracy scores. The newly created dataset is based on the eight best-fit features. All applied methods were successfully validated using the cross-validation technique. This research study has significant scientific contributions to the medical community. [10] This paper presents the development of a cyber-physical cardiac monitoring system called Big-ECG for stroke management.

The system includes a wearable ECG sensor, data storage and analysis in a big data platform, and health advisory services. The study investigated the feasibility of using ECG data to classify stroke patients with altered cardiac activity and healthy adults. The results showed that certain ECG features were significantly different between the stroke group and the control group. Machine learning algorithms were used to classify the two groups, with the Random Trees model achieving the highest classification performance. The system has the potential to assist in prognosis and rehabilitation management during post-stroke treatment. However, there are some limitations to this paper. Firstly, the study involved a relatively small sample size, with 45 stroke patients and 40 healthy adults. A larger sample size would provide more robust results. Secondly, the study only focused on ischemic stroke patients and did not include other types of stroke. Including a more diverse range of stroke patients would enhance the generalizability of the findings.

Additionally, the study did not evaluate the long-term effectiveness of the Big-ECG system in stroke management. Further research is needed to assess the system's performance and impact over an extended period of time. [11] This research paper focuses on the implementation of machine learning models to predict heart failure disease. The study aims to improve the accuracy of heart failure prediction using the UCI heart disease dataset. Multiple machine learning approaches, including decision tree, Naïve Bayes, random forest, logistic regression, and support vector machine, were used to analyze the data and predict the chances of heart failure in a medical database. The results showed that the current work improved the previous accuracy score in predicting heart disease. The integration of the machine learning model with medical information systems can be beneficial in predicting heart failure or any other disease using live data collected from patients. The algorithms used in this paper are Naïve Bayes, Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine (SVM). However, one potential limitation is the small size of the dataset used in the study. The dataset only contains records of 303 patients, which may not be representative of the entire population. Additionally, the dataset may not include all relevant variables or factors that could affect the prediction of heart failure. [12] This research paper focuses on the machine learning techniques either depend on manually extracted features or large and complex deep learning networks which merely utilize the 1D ECG signal directly. In this paper, they propose two efficient multimodal image fusion frameworks for ECG heart beat classification. They are Multimodal Image Fusion (MIF) and Multimodal Feature Fusion (MFF). For the input to these frameworks, Raw ECG data is converted into three different images using Gramian Angular Field (GAF), Recurrence Plot (RP) and Markov Transition Field (MTF). MIF performs the image fusion by combining three imaging modalities to create a single image modality which serves as input to the Convolutional Neural Network (CNN). Later MFF, extract the features from penultimate layer of CNNs and fused them for better performance of classifier. Finally, these informational features are used to train a Support Vector Machine (SVM) classifier for ECG heart-beat. This research paper focuses on an efficient machine learning-based technique needed to predict heart failure health status early and take necessary actions to overcome this issue. They developed an approach to enhance heart failure detection based on patient health parameter data involving machine learning. This study helps improve heart failure detection at its early stages to save patients' lives. They employed nine machine learning-based algorithms for comparison and proposed a novel Principal Component Heart Failure (PCHF) feature engineering technique to select the most prominent features to enhance performance. PCHF mechanism is used by creating a new feature set as an innovation to achieve the highest accuracy scores. The newly created dataset is based on the eight best-fit features. All applied methods were successfully validated using the cross-validation technique. This research study has significant scientific contributions to the medical community. [13] This paper proposes a novel classification method for arrhythmia using a three-lead multi-lead (THML) ECG data. The method utilizes a one-dimensional convolutional neural network (1D-CNN) model and a priority model integrated voting method to optimize the classification results. The experiments show that the THML ECG data improves the accuracy of arrhythmia classification, with an average accuracy of 94.4%. The proposed method also achieves high positive predictive values for the N, V, S, and F classes. The study highlights the importance of intelligent ECG recognition technology in reducing the shortage of medical resources and contributes to the intelligent dynamic research of cardiac disease. The paper proposes a hybrid approach for extracting fetal ECG signals using a combination of recursive least square (RLS) adaptive filtering and stationary wavelet transform (SWT).

The proposed system utilizes either improved spatially selective noise filtration (ISSNF) or a threshold-based denoising algorithm in the wavelet domain, resulting in enhanced fetal ECG extraction and improved signal-to-noise ratio (SNR). The effectiveness of the proposed method is evaluated using both synthetic and clinical data, and it demonstrates superior performance compared to conventional adaptive filtering techniques. [14] The proposed system offers a novel approach to fetal ECG extraction, addressing the limitations of existing techniques and providing potential improvements in prenatal healthcare. This research paper proposes a hybrid approach for extracting fetal ECG signals using a combination of recursive least square (RLS) adaptive filtering and stationary wavelet transform (SWT). The goal is to enhance the fetal ECG signal, reduce noise, and accurately detect R-peaks. The proposed

system utilizes either improved spatially selective noise filtration (ISSNF) or a threshold-based denoising algorithm in the wavelet domain. The effectiveness of the proposed method is evaluated using both synthetic and clinical data, and it demonstrates superior performance compared to conventional adaptive filtering techniques. The proposed system has the potential to extract clear fetal ECG signals with good signal-to-noise ratio (SNR) results and minimal disturbances.[15]This paper explores the generation of synthetic electrocardiogram (ECG) signals using Improved Denoising Diffusion Probabilistic Models (DDPM) and Wasserstein GAN with Gradient Penalty (WGAN-GP). The authors propose a pipeline that transforms 1D ECG time series data into a 2D space using Gramian Angular Summation/Difference Fields (GASF/GADF) and Markov Transition Fields (MTF). DDPM is then used to generate 2D 3-channel synthetic ECG images, which are de-embedded to reconstruct 1D ECG signals. The generated ECG signals are compared to real beats and WGAN-GP generated beats in terms of quality, distribution, and authenticity. The results show that WGAN-GP outperforms DDPM in all metrics, indicating its superiority in generating realistic synthetic ECG signals. By exploring the significance of ECG monitoring systems and the methodologies employed in the prediction process, this paper aims to contribute to the advancement of accurate and early detection of heart diseases.[16]This work aims to convert the ecg signal into the a 1-D signal and after accurate diagnosis it predict the heart related diseases. Effective pre-processing techniques are used for the removal of shadow from the images. Here a deep learning model is used to get a threshold value which separates ECG signal from its background and after applying various image processing techniques threshold ECG image gets converted into digital ECG. These digitized 1-D ECG signals are then passed to another deep learning model for the automated diagnosis of heart diseases into different classes such as ST-segment elevation myocardial infarction (STEMI), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), and T-wave abnormality. It also have some drawbacks to. the images acquired may contain unwanted noises which cant be resolved by the given steps. here the uniform luminance is necessary, which can be achieved by luminance correction algorithms but it does not follow the pre-processing steps, and they face errors. [17]This paper proposes an efficient prediction method for coronary heart disease (CHD) risk based on two deep neural networks (DNNs). The method involves dividing the training dataset into regular and highly biased subsets using Principal Component Analysis (PCA) and enriching the highly biased group using Variational Autoencoders (VAE). Two DNN models are then trained separately on these groups. The performance of the method is evaluated on the Korean National Health and Nutritional Examination Survey (KNHANES) dataset, and it outperforms conventional machine learning algorithms, achieving high accuracy, specificity, precision, recall, f-measure, and area under the curve (AUC) values. An automatic classifier for detecting congestive heart failure shows the patients at high risk and the patients at low risk by Melillo et al. [18]; they used machine learning algorithm as CART which stands for Classification and Regression in which sensitivity is achieved as 93.3 percent and specificity is achieved as 63.5 percent. Then for improving the performance electrocardiogram (ECG) approach is suggested by Rahhal et al. [19] in which deep neural networks are used for choosing the best features and then using them. Then, for detecting heart failures, a clinical decision support system is contributed by Guidi et al. [20] for preventing it at an early stage. They tried to compare different machine learning models and deep learning models especially neural networks, as support vector machine, random forest, and CART algorithms. An 87.6 percent accuracy was achieved by random forest and CART, which outperformed everyone used in the classification

2. CONCLUSION

This review paper has delved into the critical role the survey paper provides a comprehensive analysis of diverse learning techniques applied to heart disease prediction, highlighting their respective strengths, limitations, and potential impact. Through the comparative evaluation of various learning methodologies, including machine learning and deep learning approaches, this survey underscores the significance of leveraging advanced algorithms in the realm of heart disease prediction.

The findings reveal that machine learning techniques, such as logistic regression, decision trees, and ensemble methods, offer interpretable models and effective risk assessment based on traditional feature engineering. On the other hand, deep learning techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, demonstrate superior performance in handling complex multimodal medical data, thereby enabling more accurate predictions and early detection of heart disease.

By elucidating the strengths and limitations of different learning techniques, this survey paper not only provides insights into the evolving landscape of heart disease prediction but also offers valuable guidance for healthcare professionals and researchers. It emphasizes the potential for synergistic combinations of learning methodologies to enhance predictive accuracy and facilitate personalized risk assessment.

Ultimately, the survey underscores the transformative potential of learning techniques in advancing the field of heart disease prediction, paving the way for improved patient care, early intervention, and public health impact. Furthermore, it highlights the need for continued research and collaboration to harness the full potential of these techniques in addressing the challenges of heart disease prediction and management.

2.1 CHALLENGES FOR HEART DISEASE PREDICTION USING DIFFERENT LEARNING TECHNIQUES

Data Quality and Diversity: Access to high-quality, diverse medical data, including imaging, genetic information, and clinical records, poses a challenge for developing robust predictive models, especially when dealing with smaller or imbalanced datasets.

Interpretability: Ensuring the interpretability of predictive models, particularly with deep learning techniques, remains a challenge, as complex models may lack transparency in explaining the reasoning behind specific predictions, which is crucial for clinical acceptance.

Generalization: Achieving models that generalize well across diverse patient populations and healthcare settings is a significant challenge, as predictive models need to be robust and applicable across different demographic and clinical contexts.

Clinical Validation and Integration: Bridging the gap between research and clinical practice by validating and integrating predictive models into real-world healthcare workflows remains a challenge, requiring collaboration with healthcare providers and regulatory considerations.

Ethical and Privacy Concerns: Addressing ethical considerations, ensuring patient privacy, and maintaining data security while developing and deploying predictive models are critical challenges that require careful navigation.

Feature Engineering and Dimensionality: Extracting and selecting relevant features from complex medical data, as well as managing high-dimensional data, are ongoing challenges that impact the performance and interpretability of predictive models.

Bias and Fairness: Mitigating biases in predictive models and ensuring fairness across diverse patient populations are critical challenges that require careful consideration to avoid perpetuating disparities in healthcare.

In machine learning, a common problem is the high dimensionality of the data; the datasets which we use contain huge data and sometimes we cannot view that data even in 3D, which is also called the curse of dimensionality [21].

REFERENCES

- [1] WORLD HEALTH ORGANIZATION, Cardiovascular Diseases, WHO, Geneva, Switzerland,2020, https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1
- [2] [Shadman Nashif, Md. Rakib Raihan, Md. Rasedul Islam, Mohammad Hasan Imam](#) “Heart Disease Detection by Using Machine Learning Algorithms and a Real-Time Cardiovascular Health Monitoring System” on 4 nov 2018
- [3] Harvard Medical School, “throughout life, heart attacks are twice as common in men than women,” 2020, <https://www.health.harvard.edu/heart-health/throughout-life-heartattacks-are-twice-as-common-in-men-than-women>.
- [4] Rohit Bharti , Aditya Khamparia , Mohammad Shabaz , Gaurav Dhiman , Sagar Pande , and Parneet Singh “Prediction of Heart Disease Using a Combination of Machine Learning and Deep Learning” on 1 July 2021 Hindawi.
- [5] Hazra, A., Mandal, S., Gupta, A. and Mukherjee, A. (2017) Heart Disease Diagnosis and Prediction Using Machine Learning and Data Mining Techniques: A Review. *Advances in Computational Sciences and Technology*, 10, 2137-2159.
- [6] Cai L., Gao J., Zhao D. A review of the application of deep learning in medical image classification and segmentation. *Ann. Transl. Med.* 2020;8:713. doi: 10.21037/atm.2020.02.44. [[PMC free article](#)] [[PubMed](#)] [[CrossRef](#)] [[Google Scholar](#)]
- [7] Ras G., Xie N., van Gerven M., Doran D. Explainable deep learning: A field guide for the uninitiated. *J. Artif. Intell. Res.* 2022;73:329–397. doi: 10.1613/jair.1.13200. [[CrossRef](#)] [[Google Scholar](#)]
- [8] [vikram rajkumar](#) “Heart disease prediction using machine learning” Updated On November 28th, 2023
- [9] Azam Mehmood Qadri, Ali Raza, Kashif Munir, Mubarak S Almutairi “Effective Feature Engineering Technique for Heart Disease Prediction with Machine Learning” *IEEE Access* [2023].
- [10] Iqram Hussain and Se Jin Park “Big-ECG: Cardiographic Predictive Cyber-Physical System for Stroke Management” on 1 September 2021 *IEEE*
- [11] Fahd Saleh Alotaibi “Implementation of Machine Learning Model to Predict Heart Failure Disease” *International Journal of Advanced Computer Science and Applications*, (IJACSA) 2019.
- [12] Zeeshan Ahmad Anika Tabassum, Ling Guan and Naimul Mefraz Khan “ECG Heartbeat Classification Using Multimodal Fusion” on 15 July 2021 *IEEE Access*
- [13] Liang-Hung wang, Yan-Ting Yu, Wei Liu, Lu Xu, Chao-Xin Xie, Tao Yang, I-Chun Kuo, Xin-Kang Wang, Jie Gao, Pao-Cheng Huang, Shih-Lun Chen, Wei-Yuan Chiang and Patricia Angela R. Abu “Three-Heartbeat Multilead ECG Recognition Method for Arrhythmia Classification” on 22 April 2022 *IEEE*.
- [14] P. Darsana and Vaegae Naveen Kumar “Extracting Fetal ECG Signals Through a Hybrid Technique Utilizing Two Wavelet-Based Denoising Algorithms” on 24 August 2023 *IEEE Access*.
- [15] Edmond Adib, Amanda S. Fernandez, Fatemeh Afghah and John J. Prevost “Synthetic ECG Signal Generation Using Probabilistic Diffusion Models” on 18 July 2023 *IEEE Access*.
- [16] Siddharth Mishra, Gaurav Khatwani, Rupali Patil, Darshan Sapariya, Vruddhi Shah, Darsh Parmer, Sharath Dinesh Prathamesh Daphal and Ninad Mehendale “ECG Paper Record Digitization and Diagnosis Using Deep Learning” *Medical and Biological Engineering* (2021).
- [17] Tsatsral Amarbayasgalan, Van-Huy Pham, Nipon Theera-Umpon, Yongjun Piao and Keun Ho Ryu “An Efficient Prediction Method for Coronary Heart Disease Risk Based on Two Deep Neural Networks Trained on Well Ordered Training Datasets” on 1 October 2021 *IEEE Access*.
- [18] P. Melillo, N. De Luca, M. Bracale, and L. Pecchia, “Classification tree for risk assessment in patients suffering from congestive heart failure via long-term heart rate variability,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 727–733, 2013.

-
- [19] M. M. A. Rahhal, Y. Bazi, H. Alhichri, N. Alajlan, F. Melgani, and R. R. Yager, "Deep learning approach for active classification of electrocardiogram signals," *Information Sciences*, vol. 345, pp. 340–354, 2016
- [20] G. Guidi, M. C. Pettenati, P. Melillo, and E. Iadanza, "A machine learning system to improve heart failure patient assistance," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 6, pp. 1750–1756, 2014.
- [21] E. Keogh and A. Mueen, "Curse of dimensionality," in *Encyclopedia of Machine Learning and Data Mining*, C. Sammut and G. I. Webb, Eds., Springer, Cham, Switzerland, 2017.