

Comprehensive Review of Machine Learning Applications in Heart Disease Prediction

Yogesh Kumar¹; Geet Kiran Kaur²; Ranjit Singh³

Department of CSE Chandigarh University Chandigarh, INDIA

Abstract:- Heart infections are responsible, for deaths and now they are a major contributor to depression in many individuals. To prevent fatalities, regular monitoring and early identification of heart conditions can significantly reduce the number of deaths. Detecting heart disease has become a task in the analysis of data. While accurately predicting heart infections may pose challenges employing advanced machine learning techniques can make it easier. Studies have shown that machine learning methods can effectively predict heart disease enabling detection and assessment of its severity. This approach aims to lower mortality rates decrease the severity of the illness and facilitate diagnosis. The field of therapy is undergoing advancements through the integration of machine learning techniques leading to enhanced accuracy in interpreting analyses. These techniques play a role, in identifying indicators for predicting cardiac diseases with precision. The presentation is put together using categorization techniques, such, as Decision Tree (DT) K Nearest Neighbors (K NN) Random Forest (RF) and Support Vector Machine (SVM). The performance of these four algorithms is assessed from angles, including specificity, recall, accuracy and precision. While precision varies SVM appears to deliver the results in this approach for calculations, in many instances.

Keywords:- Heart Disease, Machine Learning, Prediction, Supervised Learning, Unsupervised Learning, Deep Learning.

I. INTRODUCTION

Cardiovascular disease as a whole including different forms, is among the principal causes of death in the global population; it comprises of coronary artery diseases, congestive heart failure, cardiac arrhythmias and valvular heart diseases. This is why, greater emphasis should be placed on detection of this disease in its early stages, so that an influx of patients does not overwhelm the medical practitioners and mortality rates soar. Though certain triggers such as heredity and age remain fixed, actual preventive measures include the use of healthy food, regular exercise, gaining control of weight and averting high blood pressure. It is vital for the public to familiarize itself with these factors in order to detect their presence and seek needed treatment on time. Preventive check and early detection forms the basis of

heart disease treatment, as there is advanced development in the diagnosis of heart diseases and well informed population. Early detection of heart disease is crucial as it can significantly improve the chances of effective treatment and reduce mortality rates (see Figure 1). The factors that cause heart diseases are also grouped into the reversible and fixed components. These are factors that cannot change biologically status and encompasses age, gender, genes among others. Again, whereas non-modifiable risk factors are beyond one's control, modifiable risk factors refer to the lifestyle factors. These include being over-weight, smoking, no exercise, poor diet, high blood pressure and high levels of cholesterol respectively. It is thus advisable to work on the alterable risk factors as a way of decreasing the prevalence and severity of heart diseases. Another difficulty that is linked intimately with heart diseases is the extent of public ignorance about these factors. This lack of knowledge, most of the time, leads to late presentation and hence delayed intervention, which is followed by severe health consequences, or even mortality. It is extensive knowledge among the medical communities and the providers in the health care industry that early detection and preventive measures are optimal when it comes to heart diseases. Heart diseases if diagnosed on time are usually manageable; however, if diagnosed at a senior stage are fatal. Better diagnosis enhanced by improved technology and knowledgeable populace will encourage early health care and intervention, better results.



Fig 1: Early Detection of Heart Disease

Often, the disease is only recognized in its final stages or after passing. This phenomenon has prompted therapeutic organizations to emphasize the importance of early disease detection.

II. LITERATURE SURVEY

Cardiovascular Diseases or CVD which includes heart diseases is a global problem and early diagnostic tools are easier to implement. Thus, the work conducted on this area with the help of Machine learning (ML) has shown the improvement of prediction accuracy and efficiency of heart diseases. This review focuses on the updated developments (last decade) in the application of methods based on the ML algorithm for diagnosing heart disease. Understanding the efficiency of these methods, comparing their results to each other, and investigating the new trends in this perspective, we only consider studies based on ML. Because in the current academic database search (IEEE Xplore, PubMed, Google Scholar) we focus on the most significant work regarding predictive models. The goal of this review is to provide those involved in research or practicing healthcare management with useful information. Relatedly, researchers will find future research directions and prospects of oil exploration and clinicians will identify ML applications and best practices for applying them to clinical practice. Thus, this review helps the ongoing processes of improving people's health and decreasing the frequency of heart diseases by pointing out those approaches that are more promising while indicating the fields that require further investigation and development.

T. Ullah et al. [1] focused on increasing the efficiency of the CVD diagnosis by choosing the best features of ECG signals which are widely employed for the automatic detection of CVD using machine learning methods. The research utilized two main datasets to detect: Another one is the Hungarian Heart Disease Dataset (HHDD) and the other one is the Behavioural Risk Factor Surveillance System (BRFSS) Dataset. The algorithms used by them were: Gradient Boosting, Logistic Regression, Extra Tree, Random Forest, Support Vector Machines (SVM), Comparison with State-of-the-Art Algorithms and Machine Learning-Based Architecture. Leveraging such techniques, the study achieved impressive accuracy rates in cardiovascular disease detection tasks.

P. Ghosh et al. [2] introduced a framework for accurate Heart Disease prediction by the different methods stressing on efficient Data Collection, Data Pre-processing and Data Transformation for model training. Using various sources of data namely Cleveland, Long Beach VA, Switzerland, Hungarian, and Stat log the study establishes suitable features through applying Relief and LASSO improving on the heart disease prediction accuracy. By applying the Decision Tree, Bayesian classifier, neural network, Association law, SVM, KNN and others, the heart diseases are detectable with good results. The proposed model in the

research paper attained the highest accuracy of 99.05% achieved by using the Random Forest Bagging Method and Relief feature selection.

S. Mondal et al. [3] which aimed at proposing a new two-tiered stacked predictive model for analysis of heart diseases risks with the use of machine learning. This model leveraged a dataset containing eleven significant characteristics from 1190 patients sourced from five distinct datasets: Some of the available datasets are the Hungarian dataset, the Cleveland dataset, the Switzerland dataset, Long Beach dataset, and the Statlog dataset. Several other ML algorithms, such as Stochastic Gradient Descent, K-Nearest Neighbor, Logistic Regression, and Random Forest have been used in the previous works to predict HD. In the context of the research paper, the proposed stacking model outperforms the works reviewed in this study in accuracy, recall, and ROC-AUC values getting to an accuracy rate of 96% and a recall of 0.98.

A. Lakshmanarao et al. [4] concerned with superior prediction of heart diseases using the state of the art machine learning integrated with better feature engineering. The experiments concerning the prediction of heart diseases were done using heart disease dataset obtained from Kaggle. This was done through association and correlation of the original dataset and consequently build up of a fused available dataset contain 29 features and 918 samples. The algorithms used were: Thus, there are K-nearest neighbours (KNN), Support vector machine (SVM), Decision tree, Random forest and XGBoost. All of these classifiers achieved a good accuracy rate for heart disease detection, ranging from 84% to 96% across different algorithms.

Gorapalli Srinivasa Rao and G Muneeswari [5] looked at how IoT, Data Mining, Deep Learning, and Machine Learning help predict heart disease. They used public datasets like UCI open dataset, Heart Disease Dataset, Cleveland heart disease dataset, and Cardiovascular Disease Dataset, plus local datasets. To predict heart disease, they tried feature selection methods such as GRAE, CAE, Lasso, IGAE, and ETC. Then, it used classifiers like Random Forest, Naive Bayes, and Gradient Boost to check if patients had heart disease. The study wrapped up by saying we need more complex systems to better spot heart disease. It stressed the value of combining different approaches.

C. M. Bhatt et al. [6] set out to examine how well different machine learning methods work to predict heart disease. The research looked at random forest, decision tree classifier, multilayer perceptron, and XGBoost algorithms. The team used a dataset of 70,000 patient records. Each record had 12 key features such as age, gender, and blood pressure readings. The models they came up with showed high accuracy: decision trees got 86.37% with cross-validation, XGBoost reached 86.87% random forest hit 87.05%, and

multilayer perceptron topped out at 87.28%. Going forward, the scientists want to check how reliable and useful these findings are. They also aim to make the results easy for people to grasp. What's more, they think it's a good idea to explore how gaps in data and weird outliers might mess with how well the models work.

A. M. Qadri et al. [7] conducted an in-depth analysis of heart-related dataset features, contributing to the understanding of key factors influencing heart disease prediction. The dataset used for the study contained 499 healthy patients and 526 patients with heart failure disease, with a distribution of 300 males and 226 females diagnosed with heart failure. Various machine learning algorithms, developed using the Python programming language-based scikit-learn library module, such as SVM, random forest, decision tree, logistic regression, and naïve Bayes classifier were used to predict heart failure. The decision tree method emerged as the top-performing model, achieving an impressive accuracy score of 100% in heart failure prediction, surpassing other machine learning algorithms and highlighting the success of the proposed feature engineering approach.

P. Rahman et al. [8] attempted to develop a machine learning tool based on various machine learning algorithms together with artificial neural networks (ANNs) for the prediction of heart failure risk which can ensure early diagnosis and cost effective treatment. The age of dataset from research was an average 65 years old, showing real patient demographics affected by cardiovascular diseases with a minimum recorded as low as 42 and maximum even higher than that at the astonishing number of over 95. In the present study, a combination of various supervised learning classifiers such as KNN, SVM, DT, RF and xgBoost/RandomForest, xgBoost/CatBoost was used to develop a highly stable accurate model. The results highlighted the importance of a predictive modeling early detection for heart failure to control effectively the cardiovascular diseases world epidemic.

J. Rashid et al. [9] aimed at identifying relevant input features based on the brute-force algorithm and by introducing machine learning techniques to improve heart disease Classifier. The research paper uses three datasets of heart disease named the Cleveland, Statlog and Hungary datasets which are extracted from University Of California-Irvine ML repository. The heart disease prediction can be improved using machine learning techniques like Support Vector Machine (SVM), Random Forest, K Nearest Neighbor (KNN) and Naive Bayes. Relative to the results of split validation, the accuracy with Naive Bayes reached 97% whereas that caused by Random Forest via cross-validation was about 95%.

N. Lutimath et al. [10] focused on the machine learning techniques to predict heart disease using biomedical data. The data set on proof is taken to his website of heart diseases dataset, Diabetes Mellitus and Liver disease COSTNTAX (video interpretation): Dataset: 600 records were part of this, having a high accuracy rate to about 98% accurately predicted). These classification methods are used in this paper: Decision Tree, Support Vector Machines and Random Forest model. This paper compares the random forest regression model to decision tree regression based on classification, feature engineering, and performance measures. From this study we find that of decision tree regression model and random forest regression model the results are more accurate in case of prediction heart disease by using Random Forest as compared to Decision Tree model.

N. Alageel et al. [11] aimed to increase the accuracy of predicting a stroke in the medical field due to Machine and deep learning technologies have been made. Datasets from kaggle, EHRs were used to predict stroke with many features without and with age, BMI, glucose level, and smoking status. The following machine learning algorithms have been employed in this research, among others: Naïve Bayes, SVM, Decision Tree, Random Forest, K-Nearest Neighbours (KNN), and Stacking. Thus the application showcases the importance of benefiting simple algorithms, which demonstrate high accuracy with explainable outcomes, than complex algorithms.

M. K. Joshi et al. [12] intended to compare the performance of different Machine learning algorithms in predicting cardiovascular indices, emphasizing on using data driven methods for early detection and ultimatum of disease. The used datasets such as Cleveland dataset from the UCI ML repository and PIMA dataset to train and test their machine learning model for prediction of cardiovascular disease. The methodologies involve implementing deep neural networks, KNN and SVM-based models, decision trees with random forest classifiers, logistic regression model along with Naive Bayes classifier and support vector classifier. For heart disease prediction novel method like MSSO-ANFIS has been introduced here, and therefore, feature selection methods such as LCSA show higher accuracy with lower error rate.

➤ *Machine Learning in Healthcare*

Machine learning (ML) involves algorithms that allow computers to learn from and make predictions on data. In healthcare, ML can analyze large datasets to uncover patterns and make predictions. ML methods are increasingly being used for disease prediction, including heart disease.

III. TECHNIQUES FOR HEART DISEASE PREDICTION

A. Supervised Learning Methods

- **Logistic Regression:** Logistic regression is used for binary classification problems. It is simple and interpretable, making it a common choice for medical predictions.
- **Decision Trees:** Decision trees partition data into subsets based on feature values. They are easy to interpret but prone to overfitting.
- **Random Forest:** Random forest is an ensemble method that builds multiple decision trees and merges their results to improve accuracy and control overfitting.
- **Support Vector Machines:** Support vector machines (SVM) find the hyperplane that best separates different classes in the feature space. They are effective in high-dimensional spaces.
- **k-Nearest Neighbors:** k-Nearest Neighbors (k-NN) classify data points based on their proximity to other points. It is simple but can be computationally intensive.
- **Neural Networks:** Neural networks consist of layers of nodes that mimic the human brain. They can model complex relationships but require large datasets and computational power.

B. Unsupervised Learning Methods

- **Clustering:** Clustering algorithms like k-means and hierarchical clustering group data points based on similarity, which can reveal patterns in heart disease data.

C. Ensemble Methods

- **Bagging:** Bagging, or Bootstrap Aggregating, improves the stability and accuracy of machine learning algorithms by combining the predictions of multiple models.
- **Boosting:** Boosting sequentially applies models to improve weak predictions, commonly used algorithms include AdaBoost and Gradient Boosting.

D. Deep Learning Methods

- **Convolutional Neural Networks:** Convolutional Neural Networks (CNNs) are effective for image data, useful in analyzing medical imaging for heart disease.
- **Recurrent Neural Networks:** Recurrent Neural Networks (RNNs) handle sequential data, such as time series of patient vitals, to predict heart disease trends.

IV. PROPOSED METHODOLOGY FOR HEART DISEASE PREDICTION

This section outlines the methodology used to develop a prediction model for identifying individuals at risk of heart disease. The approach encompasses a series of steps for data collection, preparation, analysis, and evaluation to construct an effective prediction model. The methodology provides a comprehensive framework for conducting a thorough and productive study as shown in Figure 2.

A. Data Collection

➤ *Effective Heart Disease Prediction Begins with the Collection of Relevant Patient Data. This Data Typically Includes:*

- **Medical Histories:** Patient health records detailing past medical conditions and treatments.
- **Demographic Information:** Age, gender, ethnicity, and other demographic factors.
- **Clinical Measurements:** Blood pressure, cholesterol levels, blood sugar levels, and body mass index.
- **Lifestyle Factors:** Smoking status, physical activity levels, dietary habits, and family history of heart disease.

B. Preprocessing

➤ *Preprocessing is Essential to Ensure the Quality and Consistency of the Dataset. The Steps Involved are:*

- **Data Cleaning:** Address missing values, correct inconsistencies, and handle outliers.
- **Normalization:** Scale features to ensure uniformity across different attributes.
- **Data Splitting:** Divide the dataset into training and testing subsets, typically using an 80:20 ratio.

C. Feature Selection

Feature selection involves choosing the most relevant features for the predictive model. Techniques used for feature relevance based on their relationship with the target variable.

- **Information Gain:** Measures how much a feature improves the prediction of the target variable.

➤ *Wrapper Methods:*

- **Forward Selection:** Starts with an empty set and adds features based on model performance.
- **Backward Elimination:** Begins with all features and removes them iteratively based on performance.
- **Recursive Feature Elimination (RFE):** Removes features iteratively to find the best subset.

➤ *Embedded Methods:*

- **Lasso Regression:** Uses L1 regularization to shrink some coefficients to zero, performing feature selection during training.
- **Decision Trees:** Provides feature importance scores that help in selecting relevant features.

➤ *Ensemble Methods:*

- **Feature Importance from Ensemble Models:** Algorithms like Random Forest and Gradient Boosting provide scores based on feature contribution to predictions.

D. Model Testing

➤ *Testing Ensures the Model's Robustness and Applicability by:*

- **Evaluation on Test Data:** Assessing model performance on unseen data to verify its predictive accuracy.
- **Performance Metrics:** Evaluating metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to gauge model effectiveness.

E. Results and Analysis

➤ *Researchers Analyze the Model's Performance to:*

- **Performance Evaluation:** Determine how well the model predicts heart disease and classifies patients.
- **Comparative Analysis:** Compare results across different models and techniques to identify the most effective approach.
- **Visualization:** Use graphical tools and flowcharts to illustrate methodology and results.

V. MODEL EVALUATION AND PERFORMANCE METRICS

Model evaluation is crucial for assessing the performance of predictive models. Various metrics are used to measure the effectiveness of models in predicting heart disease. Here, we discuss several key metrics and their formulas.

A. Accuracy

Accuracy measures the proportion of correctly classified instances out of the total instances. It is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where:

- TP = True Positives

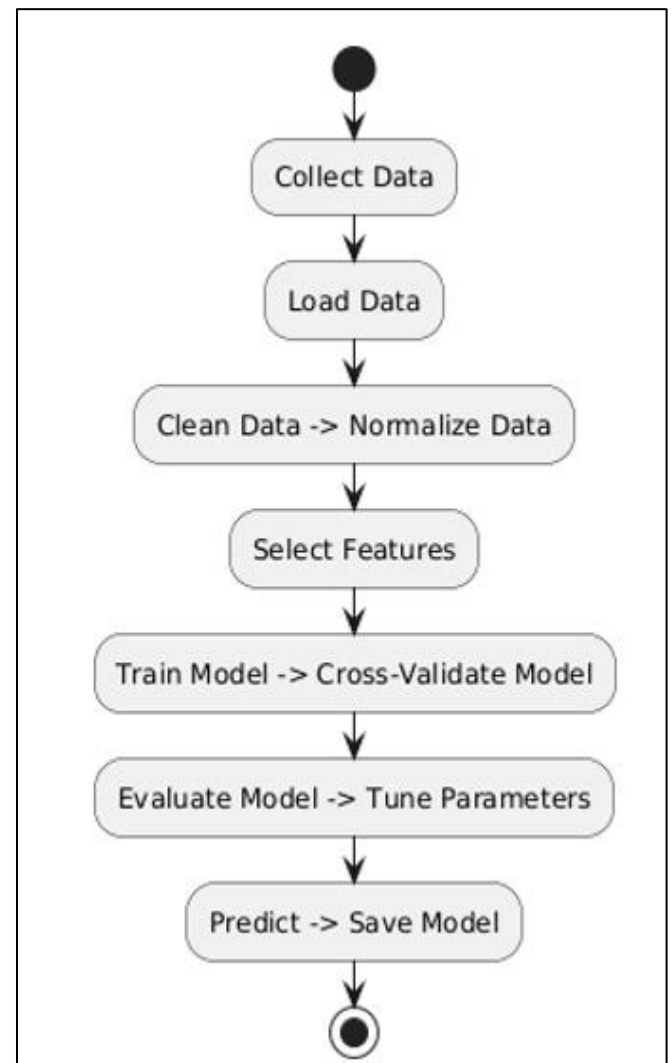


Fig 2: Flowchart Depicting the Methodology for Heart Disease prediction

- TN = True Negatives
- FP = False Positives
- FN = False Negatives

B. Precision

Precision, also known as Positive Predictive Value, measures the proportion of true positives out of the total predicted positives. It is given by:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (2)$$

C. Recall

Recall, also known as Sensitivity or True Positive Rate, measures the proportion of true positives out of the total actual positives. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3)$$

D. F1-Score

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both. It is defined as:

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

E. AUC-ROC

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures the performance of a classification model by evaluating its ability to distinguish between classes. The ROC curve plots the True Positive Rate (Recall) against the False Positive Rate (1 Specificity) at various thresholds. The AUC is the area under this curve, with a value between 0 and 1. Higher AUC values indicate better model performance:

$$\text{AUC-ROC} = \int_{-\infty}^{\infty} \text{ROC}(t) dt \quad (5)$$

F. Cross-Validation

Cross-validation is a technique used to ensure the robustness and generalizability of the model. It involves partitioning the data into training and validation sets multiple times to assess model performance consistently. The most common method is k-fold cross-validation, where the data is split into k subsets, and the model is trained k times, each time using a different subset as the validation set and the remaining data as the training set. The overall performance is averaged over all folds to obtain a robust estimate.

VI. RESEARCH GAPS

- **Inaccurate Early Detection:** The current diagnostic tools, such as ECGs and stress tests are great so far but they frequently overlook the subtle manifestations of early-stage heart problems causing underdiagnosis where potential conditions go undetected or overdiagnosis that can spawn more unnecessary testing and interventions. This emphasises the requirement of improved and nuanced methods that integrate machine learning/AI with large datasets for increased sensitivity, specificity, and consequently early diagnosis without biopsy may assist in earlier patient outcomes.

- **One-Size-Fits-All Risk Assessment:** Traditional cardiac risk models are fundamentally flawed since they are using generic data yet to examine the billions of possibilities. This ignores factors such as personal lifestyle habits (diet, activity levels, stress), genetic influences and even socioeconomic status - all of which also play a large role in cardiovascular health. To combat this, individualized risk models are currently being tailored. By taking personal data into account, these models offer more individualized calculations of risks and can deliver risk targeted approaches for patients identified with higher levels of genetic predisposition to the disease.
- **Untapped Potential of Remote Monitoring:** Despite being promising, wearable technology & smartphone apps have a long way to go for effective accomplishment of continuous heart health tracking. These are devices that can measure heart rate, blood pressure and oxygen levels live as well as data points regarding the way a person is living day to day. Efforts are underway to improve the data that can be provided by these wearable - ideally in a way people could stand wearing them all day. This ongoing monitoring can help people manage the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) measures the performance of a classification model by evaluating its ability to distinguish between their heart health before issues occur, the company said. In conclusion, remote monitoring has the potential to enhance external access and convenience of cardiac care.
- **Limited Prediction Accuracy:** The trouble with data analysis today is that while technology can analyse the needs of manufacturing lines, it will struggle when it comes to making sense out of masses complex and varied patient information. Which either then leads to the missing of high-risk people or raising a bunch of false alarms. One answer lies in deep learning enabling the efficient processing of complex data sets. Deep learning can provide substantial performance gains by recognizing subtle patterns and narrowing the field down to select key data points for better prediction centres.

VII. CHALLENGES AND LIMITATIONS

- **Data Obstacles:** The datasets tend to be imbalanced with a higher number of records from healthy patient than those with heart diseases. This leads to situations where the AI models are extremely good at prediction of healthy people but entirely miss out on heart disease. HE often entails missing and sometimes conflicting or incorrect medical data. This causes what is referred to as 'noisy' data to be generated and this makes the AI predictions to be wrong. Cleaning data is very important for any machine learning and artificial intelligence models.

- **Ethical Considerations:** The protection of patients' information as well as the effectiveness of results derived from big data and machine learning in the health sector is challenging. Despite its usefulness for developing accurate AI models, patient data is not readily available due to regulatory restraints such as HIPAA and GDPR. Others are the ethical issues that include, informed consent and the clear statement on how data will be used. Patient data is the main ingredient used in designing and implementing an AI system in healthcare, and such data needs to be trusted to ensure proper usage.
- **Model Development & Integration:** Applying of machine learning models to practical clinical work means multiple stages of work. First, real-world testing of interventions makes it possible to enhance the safety of ventures and their efficiency. But before that, the most appropriate method of adopting machine learning is selected depending on the problem and data type. Clinicians must comprehend why the model's prediction are accurate in assessing the patient; lastly, integration with the existing health-care concept and electronic medical records greatly enhances the chances of the model's successful implementation.
- **Long-Term Challenges:** Despite the successful development, the long-term problems of applying machine learning models to cardiac diagnosis remain topical. This flexibility is required due to the constant changes with the patient demographics, the methods of treatments, and interpreting changing rules and laws. This ensures models are not outdated, invalid or may infringe on patient's rights for long term sustainable management of diseases.
- **Scalability & Sustainability:** The effectiveness and safety of the algorithms to use in diagnosing heart diseases, depend on their applicability for real-life use. This makes it necessary to carry out tests to establish the efficacy particularly in the diverse patients and scenarios. Thirdly, the models require constant updating of data to be effective; this can prove cumbersome at times. Last but not the least, it is necessary to invest financial resources and personnel time in the long term to routinely check the models' validity and update and fine-tune the models.

VIII. RECENT ADVANCES AND FUTURE DIRECTIONS

Machine learning is revolutionizing heart disease prediction. Real-time data from wearables and internet-connected devices allows for continuous patient monitoring, enabling models to adapt to changing health conditions and make dynamic predictions. Deep learning techniques like Convolutional Neural Networks and Recurrent Neural Networks excel at handling complex medical data such as images and time-series information. This leads to improved feature extraction and overall model performance. Additionally, data fusion techniques are bringing together information from electronic health records, genetics, and

lifestyle data to create a more comprehensive picture of patient health, resulting in more accurate predictions. To build trust and transparency, researchers are developing methods like SHAP and LIME that provide insights into how models reach their conclusions. Finally, hybrid models that combine traditional machine learning with deep learning leverage the strengths of both approaches to enhance prediction accuracy and reliability.

Looking ahead, the future of heart disease prediction with machine learning is bright. Continuous monitoring through real-time data streams holds promise for even better predictions and enabling proactive interventions. Exploring advanced deep learning techniques remains a key area of interest, with the potential to further improve feature extraction and model performance. Personalized prediction models that consider individual variations in genetics, lifestyle, and environmental factors are another exciting avenue for research. Ultimately, the success of these models hinges on their interpretability and usability in clinical settings. Developing user-friendly tools and making models more transparent will be crucial for their seamless integration into healthcare workflows.

IX. CONCLUSION

This review paper aims at giving a systematic review of several machine learning models that are applied in predicting the odds of cardiac ailments and noting notable developments for early detection of the ailments and treatment performance. The use of machine learning approaches has been of great help in improving the chance of predicting cases of heart disease through proper sorting of the risk factors with the help of big data. The ability of ML algorithms to sift through large amounts of data from different sources can uncover potentially unseen risk factors where conventional means fail, thus detecting and inhibiting before an event occurs probably saves lives. The research emphasizes the critical need for ML in addressing this growing epidemic of heart disease.

Some of the promising directions of further development of ML for improving the assessment of the risk of cardiac diseases are described in the paper. The potential to further enhance precision and clinical relevance lies in real-time monitoring via wearables, advanced deep learning algorithms trained across clusters of patients, as well as personalized models. But broader adoption requires resolving issues including interpretability for clinicians and integration into existing healthcare workflows. The paper also argues that rigorous innovation of machine learning models, transparency about their predictions and integration into the clinical workflow is critical going forward. Altogether, these advances have considerable promise for improved diagnostics that are finer and more accurate- potentially saving lives worldwide by helping to alleviate the burden of cardiovascular diseases.

REFERENCES

- [1]. T. Ullah, S. I. Ullah, K. Ullah, M. Ishaq, A. Khan, Y. Y. Ghadi, and A. Algarni, "Machine learning-based cardiovascular disease detection using optimal feature selection," *IEEE Access*, vol. 12, p. 16431–16446, 2024. [Online]. Available: <http://dx.doi.org/10.1109/ACCESS.2024.3359910>
- [2]. P. Ghosh, S. Azam, M. Jonkman, A. Karim, F. M. J. M. Shamrat, E. Ignatious, S. Shultana, A. R. Beeravolu, and F. De Boer, "Efficient prediction of cardiovascular disease using machine learning algorithms with relief and lasso feature selection techniques," *IEEE Access*, vol. 9, p. 19304–19326, 2021. [Online]. Available: <http://dx.doi.org/10.1109/ACCESS.2021.3053759>
- [3]. S. Mondal, R. Maity, Y. Omo, S. Ghosh, and A. Nag, "An efficient computational risk prediction model of heart diseases based on dual-stage stacked machine learning approaches," *IEEE Access*, vol. 12, p. 7255–7270, 2024. [Online]. Available: <http://dx.doi.org/10.1109/ACCESS.2024.3350996>
- [4]. Lakshmanarao, T. V. Sai Krishna, T. S. Ravi Kiran, C. V. Murali krishna, S. Ushanag, and N. Supriya, "Heart disease prediction using ml through enhanced feature engineering with association and correlation analysis," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 2, p. 1122, May 2024. [Online]. Available: <http://dx.doi.org/10.11591/ijeecs.v34.i2.pp1122-1130>
- [5]. Srinivasa Rao and G. Muneeswari, "A review: Machine learning and data mining approaches for cardiovascular disease diagnosis and prediction," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 10, Mar. 2024. [Online]. Available: <http://dx.doi.org/10.4108/eetpht.10.5411>
- [6]. C. M. Bhatt, P. Patel, T. Ghetia, and P. L. Mazzeo, "Effective heart disease prediction using machine learning techniques," *Algorithms*, vol. 16, no. 2, p. 88, Feb. 2023. [Online]. Available: <http://dx.doi.org/10.3390/a16020088>
- [7]. M. Qadri, A. Raza, K. Munir, and M. S. Almutairi, "Effective feature engineering technique for heart disease prediction with machine learning," *IEEE Access*, vol. 11, p. 56214–56224, 2023. [Online]. Available: <http://dx.doi.org/10.1109/ACCESS.2023.3281484>
- [8]. P. Rahman, A. Rifat, M. IftehadAmjad Chy, M. Monirujjaman Khan, M. Masud, and S. Aljahdali, "Machine learning and artificial neural network for predicting heart failure risk," *Computer Systems Science and Engineering*, vol. 44, no. 1, p. 757–775, 2023. [Online]. Available: <http://dx.doi.org/10.32604/csse.2023.021469>
- [9]. J. Rashid, S. Kanwal, J. Kim, M. Wasif Nisar, U. Naseem, and A. Hussain, "Heart disease diagnosis using the brute force algorithm and machine learning techniques," *Computers, Materials amp; Continua*, vol. 72, no. 2, p. 3195–3211, 2022. [Online]. Available: <http://dx.doi.org/10.32604/cmc.2022.026064>
- [10]. N. Lutimath, N. Sharma, and B. K, "Prediction of heart disease using biomedical data through machine learning techniques," *EAI Endorsed Transactions on Pervasive Health and Technology*, p. 170881, Jul. 2018. [Online]. Available: <http://dx.doi.org/10.4108/eai.30-8-2021.170881>
- [11]. N. Alageel, R. Alharbi, R. Alharbi, M. Alsayil, and L. A. Alharbi, "Using machine learning algorithm as a method for improving stroke prediction," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 4, 2023. [Online]. Available: <http://dx.doi.org/10.14569/IJACSA.2023.0140481>
- [12]. M. K. Joshi, D. Dembla, and S. Bhatia, "Prediction of cardiovascular disease using machine learning algorithms," *International Journal of Advanced Computer Science & Applications*, vol. 15, no. 3, 2024.