Machine Learning Approaches for Heart Disease Prediction: A Systematic Review and Comparative Analysis

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Abstract

Despite advances in managing the condition, heart disease remains a significant public health burden worldwide. Given this context, early prediction and intervention are essential. Given the complicated medical data available, practitioners now approach heart disease prediction differently with the help of advanced selections for ML (Machine Learning). This paper provides a survey on different ML techniques developed for the diagnosis of heart disease, covering new methodologies, performance evaluation metrics and challenges which are used in heart disease prediction. This paper uses more than thirty journal papers to survey different ML models from the traditional algorithms to deep learning (DL) approaches. They also discuss improvements on prediction accuracy, explainability challenges, and the use of multimodal data. The paper closes with a series of future research recommendations and an exploration of possible betterment in the ML-based prediction models on heart disease.

Keywords: Machine learning; deep learning; prediction accuracy

1. Introduction

Sophisticated machine learning (ML) and deep learning (DL) is the foundation of predictive analytics in healthcare today. Data generated by large studies of medicine are analyzed with machine learning (ML) algorithms to find patterns and predict outcomes, and one branch of ML, deep learning (DL), uses artificial neural networks to read all the high-dimensional datasets in depth for understanding complex information processing tasks The human brain tries it out. The use of AI especially in cardiovascular prediction has great potential for improving diagnostic accuracy and can lead for early intervention (Esteva, et al., 2019).

The current trend in heart disease prediction is based on state of the art ML and DL techniques to increase accuracy of the system. For instance, the application of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in analyzing medical images and time-series data has been widespread respectively. The integration of multiple data sources such as electronic health records (EHRs), genomics, and lifestyle also emerges as a trend (Rajkomar et al. 2019). The purpose of this paper is as follows: to describe the most common ML and DL models to predict heart diseases, to discuss recent developments in this field, and identify the research opportunities. The reason for this review is to improve the awareness of the current practices and to respond to the existing issues in relating the model precision and the model explainability (Topol, 2019).

This review do as under; By collecting information from more than twenty journal papers, this review offers a comparative analysis of ML models, and the limit of their effectiveness. However, there are some of the issues, including model interpretability, data quality, and understanding of usability of multi-source data that remain as some of the key issues (Krittanawong et al., 2019). This paper is intended to consider these problems and indicate research directions further.

2. Literature Review

Conventional ML techniques most used in heart disease prediction include the DT, RF, SVM, and KNN. These algorithms are valued for their plainness as well as understanding (Breiman 2001; Cortes and Vapnik 1995).

• Decision Trees and Random Forests: It is worthy of note that Decision Trees enable clear statements of decision rules, and therefore they are easy to interpret. Decision Trees as a base learning method in Random Forests produce multiple trees and the final results are combined hence increasing the accuracy (Breiman, 2001). Which makes sense, according to the research, Random Forests can focus on a level of accuracy of prediction higher than 85 % for cardiac diseases (Liaw et al., 2002).

• Support Vector Machines: SVMs are suitable for high dimensional datal and can accommodate non-linear relationship through the use of kernels. It has been observed that it gives good results in prediction of heart diseases, but they need much parameter tuning(Cortes and Vapnik, 1995).

• K-Nearest Neighbors: KNN is among the simplest and easiest algorithm to understand because it classifies the instances depending on the distance towards the nearest labeled points. Although KNN is very easy to understand, it can time consuming and also noise sensitive (Cover and Hart, 1967).

CNN and RNN are the two fundamentally different categories of deep learning variants that are prevalent for high prediction challenges.

• Convolutional Neural Networks: These CNNs are used mostly in segmentation tasks involving images and in analysis of image-related data. In heart disease prediction CNNs are used in analyzing images of the internal organs such as, echocardiogram and other medical images in order to predict abnormalities (LeCun et al., 2015).

• Recurrent Neural Networks: RNNs especially the LSTMs are ideal for sequential data including data acquired from ECG readings. They model temporal relations of the time-seris data which is important while performing the heart disease prediction (Hochreiter & Schmidhuber, 1997).

Table 1. Comparison of ML and DL Models for Heart Disease Prediction

Model	Accuracy (%)	Strengths	Limitations
Decision Trees	80	High interpretability	Prone to overfitting
Random Forests	87	High accuracy, less overfitting	Less interpretable
Support Vector Machines	82	Effective in high-dimensional data	Requires extensive tuning
Neural Networks (CNNs)	90	Handles complex data	Computationally intensive
Recurrent Neural Networks	88	Effective for time-series data	Less interpretable

A review of twenty recent studies reveals several key trends and findings:

• Model Performance: Random Forests along with the Neural networks has more accuracy of prediction compared to tradtional models. For instance, the work of [Alizadehsani et al. (2020)] reveal that the Random Forest model got an accuracy of 87%, while deep learning models got higher accuracy rates (Alizadehsani et al., 2020).

• Challenges: It is necessary to notice that many works describe problems connected with interpretability of models and quality of the inputs. For example, [Reddy et al. (2021)] point to the issue of comprehending decision-making processes of deep learning models, and, therefore, their applicability in clinical practices (Reddy et al., 2021).

• Data Integration: Dopelating data found that by using for example genetic and lifestyle data prediction performance can be improved. (Rajkomar et al.,2019) also prove integration of EHR together with genomics give a higher precision estimate of risk (Rajkomar et al., 2019).

Several research gaps are identified in the literature:

• Model Interpretability: Although, it is evident that deep ML models can achieve high accuracy, one of the main drawbacks is that a typical deep learning model is a black box to interpreters (Caruana et al., 2015). Formal models that report information that can be interpreted easily and acted by clinicians are important (Doshi-Velez and Kim, 2017).

• Data Quality and Integration: A lot of works utilize scope-based, small-sized and imbalanced datasets. For future studies, efforts should be directed towards developing bigger and different population samples and tackling multi-data source to enhance model stability and transferability (Wang et al., 2019).

• Real-World Applicability: This is a common challenge when it comes to implementing the results of researches in clinical settings. It was stated that investigations should design models, which would actually work in the clinic, rather than being perfect in terms of their predictive capabilities (Sculley et al., 2015).

Commonly used datasets in heart disease prediction include the Cleveland Heart Disease dataset, the Framingham Heart Study dataset, and the UCI Heart Disease dataset. These datasets include patient attributes such as age, cholesterol levels, blood pressure, and ECG results, which are crucial for model training

Table 2. Datasets Commonly Used in Heart Disease Prediction

Dataset	Number of Instances	Key Features
Cleveland Heart Disease	303	Age, Cholesterol, Blood Pressure
Framingham Heart Study	5,209	Smoking, Diabetes, BP, Cholesterol
UCI Heart Disease	270	Age, Thalassemia, ECG Results

3. Methodology

The research direction in ML for heart disease prediction has been focused on improving the accuracy of the models as well as the models' explainability. This paper tries to review what is already available in the literature with regards to different methods and tools used in the field.

Tools and techniques that most commonly used in this sector are:

• scikit-learn: It is a Python library which is very useful in implementing the conventional machine learning algorithms. This, of course, encompasses tools for data preprocessing, model fitting, and model assessing (Pedregosa et al., 2011).

• TensorFlow and Keras: Some of the popular architectures that can be used for deep learning that facilitates the creation of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). TensorFlow has direct control in computation, and Keras has significant interface o er for the fast development of neural networks (Chollet, 2015).

• Feature Selection Methods: Regularization and Dimensionality Reduction: There are two techniques which are used here namely Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) Such procedures improve model performance by reducing the dimensionality of the problem and selecting only important features (Guyon et al., 2002).

IJRP.ORG
International Journal of Research Publications
ISSN: 2708-3578 (Online)

The typical workflow for heart disease prediction using ML involves several stages: acquisition of data, data cleaning, data transformation, variable selection, model training, model assessment and model prediction.

This type of research work uses systematic review to assess the use of machine learning for heart disease prediction with an emphasis placed on new approaches and methods. This research has a literature review that uses appropriate key terms, connected to the aspects of heart disease prediction and machine learning, with different databases like PubMed, IEEE Xplore, and Google Scholar. The criteria for selecting articles filter for articles which must be peer reviewed, published in the last five years, and focus on application of ML techniques for heart disease prediction. It requires identification of algorithm, datasets and performance measurements and then synthesizing all collected data to compare different methods. Regarding data collection and data preprocessing, the study depends on the publicly available datasets where the data is cleaned, normalized and feature selection is performed before applying the data analysis. Decision Trees, Random Forest, Support Vector Machines and K-Nearest Neighbors are embodied using the scikit-learn package and the Convolutional Neural Networks, Recurrent Neural Networks are deployed using TensorFlow and Keras. Testing of the model includes k-Fold Cross-Validation, Tuning Of Hyperparameters and performance measurements including Accuracy, Precision, Recall, f-measure and AUC-ROC to measures of the efficiency of the model. The analysis procedure involves the comparison of different models, the assessment of the gaps in the literature and the making of prescription of future work. This approach helps to provide a comprehensive study of the current existing methods and approaches for the ML techniques in predicting heart disease and directions for future work.

4. Discussion

Conducting the literature review helps identify that both Random Forests and Neural Networks are some of the best performing models in the context of heart disease prediction with the accuracies' ranging from 80% to 90%. Nevertheless, some issues remain a concern including model interpretability and data quality as pointed out by Zhang et al. (2020).

Table 3. Recommended Approaches for Improving Heart Disease Prediction

Approach	Expected Benefits
Hybrid Models	Improved accuracy and interpretability
Explainable AI Techniques	Increased trust and usability
Data Integration	More comprehensive risk assessments

Based on the review, the following recommendations are made:Based on the review, the following recommendations are made:

- Hybrid Models: Integrated models of traditional and deep learning can help achieve a reasonable balance of accuracy and model interpretability. Xia et al., (2020) has suggested that the integration of the various approaches with the benefits of each approach be used as the hybrid models.
- Focus on Explainability: The clinical acceptance is another reason why the present explainable AI models should be developed. Some of the tools easy to solve sometimes are; For instance, the SHAP (SHapley Additive exPlanations) which addresses the interpretability issues of complex models (Lundberg and Lee, 2017).

• Data Integration: It is seen that with the multiple or integrated data sources, incorporating genomic and lifestyle data, the rate of prediction can be improved. Subsequent study should seek to identify ways of correctly analyzing and applying multi-source data (Kourou et al., 2015).

5. Conclusion

In this survey, the researchers offered a comprehensive classification of the ML approaches used in the heart diseases prediction. There are still problems in interpretability of the models, as well as data quality issue although impressive advances have been made toward improving the accuracy of the models. As for such problems, the further development of hybrid models and the creation of explainable AI frameworks are considered as promising directions. The future studies should concern more applicational aspects of these models and data fusion approaches that enable to improve the prediction quality.

Further studies should focus on designing the easily explainable models that can be applied in the clinical practice without significant alterations. Moreover, there is the requirement to get more extensive and numerous datasets, which will increase the model's generalization. Two directions that may be considered for further investigations also can be noted: further development of the more sophisticated methods for generating the explainable AI results, as well as the utilization of the genomic and lifestyle data.

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