A Review on Deep Learning Approaches in Detecting Cardiovascular Disease

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ABSTRACT

Cardiovascular diseases (CVDs) continue to be the top cause of death globally, responsible for almost a third of all fatalities. Timely and precise prediction of CVD risk is essential for efficient prevention, prompt intervention, and alleviating healthcare strain. Recently, deep learning (DL) has become a robust framework that can uncover intricate, non-linear patterns from various medical data sources, such as electronic health records, electrocardiograms (ECG), imaging techniques like echocardiography and retinal fundus, along with data from wearable sensors. Cutting-edge architectures like convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), and transformer models have shown enhanced predictive capabilities when compared to conventional machine learning techniques. Additionally, hybrid methods that merge DL with optimization techniques or ensemble strategies improve model robustness and generalization. Nevertheless, hurdles persist concerning data imbalance, interpretability, and clinical validation. To overcome these constraints, recent studies have integrated explainable AI (XAI) tools, multimodal data integration, and Internet of Medical Things (IoMT)-enabled real-time monitoring systems. This study emphasizes existing deep-learning methods used for CVD prediction, assesses their performance on different datasets, and addresses unresolved research issues such as scalability, fairness, and incorporation into clinical settings.

Keywords: Cardiovascular disease (CVD), Heart Disease prediction, Deep learning (DL), Convolutional neural networks (CNN), Recurrent neural networks (RNN), Long short-term memory (LSTM), Transformer models, Hybrid model.

1. INTRODUCTION

Cardiovascular disease is a significant worldwide health issue, responsible for approximately 17.9 million fatalities each year, which represents 31% of all deaths globally. Anticipating heart disease is essential, as it can help alleviate its severe effects on individuals and healthcare systems. Early diagnosis can enhance patient outcomes by preventing complications and decreasing mortality rates. Predictive models can also assist healthcare professionals in optimizing resource allocation and tailoring treatment approaches, thus improving the efficiency of healthcare delivery. Given that heart disease is a leading cause of mortality worldwide, there is a need for effective predictive models to facilitate early detection and intervention strategies. Progress in Machine Learning (ML) has resulted in the creation of precise models for forecasting cardiovascular outcomes based on patient information [1]. Based on information from the World Health Organization (WHO), cardiovascular disease poses a significant risk to global health. Various elements can lead to CVDs, including high blood pressure, obesity, high cholesterol levels, diabetes, and arrhythmias. A majority of individuals affected by cardiovascular disease end up losing their lives because they were not diagnosed properly in the early stages [2].

The ECG shows the heart's rhythm and electrical activity and is printed on paper. Doctors or heart specialists use this paper printout to look at different aspects by hand, such as heart rate, rhythm, shortness of breath, how electrical signals move through the heart, and any unusual signs that might show a problem with the heart. However, looking at an ECG by hand takes a lot of time and can be difficult. Sometimes it can also be wrong, which can be very dangerous. In such cases, deep learning and improvements in computer vision and image analysis have changed how medical images are studied. Especially, convolutional neural networks (CNNs) have shown great ability to find detailed patterns and features in medical images, helping in accurate disease prediction and classification. CNNs can automatically learn different levels of features. They learn directly from the images using several layers. The earlier layers find simple things like edges and textures, while the later layers recognize more complex things like shapes and areas. They can also find the specific patterns that show problems in ECG images [3,4].

In this article, an analysis of various algorithms related to heart disease prediction is carried out to find a more efficient algorithm for heart disease prediction. The important purpose of this article is studying in detailed information about most suitable algorithm for heart disease prediction. In addition, their limitations are addressed to further improve the lung cancer detection.

2. SURVEY ON CARDIO DETECTION TECHNIQUES

Subramani et al. [5] introduces a combined method that brings together traditional machine learning classifiers like SVM, logistic regression, decision trees, and random forests with deep learning models such as CNNs and RNNs. It explains how IoT devices and ongoing monitoring can collect a lot of data for better predictions. The research shows that using a mix of these models usually works better than using just one type of algorithm. It also talks about real-world challenges like making the models work on a larger scale and ensuring they are useful in a medical setting.

Khan et al. [6] and their team proposed a study about using machine learning to predict cardiovascular disease. They used several types of classifiers, including Logistic Regression, SVM, Decision Tree, Random Forest, KNN, and Naïve Bayes, on a clinical dataset. Their results showed that Random Forest and SVM worked the best, with accuracy higher than 85%. The paper talks about how choosing the right features can help improve the performance and accuracy of these models. However, they also mention some drawbacks, like the dataset being too small, not using deep learning techniques, and not including explainable AI methods. In general, the study shows that machine learning, especially models that combine multiple techniques, can help find cardiovascular disease early and support doctors in making treatment decisions.

Zhou et al. [7] presents a comprehensive review of deep learning models for heart disease prediction, examining CNNs, RNNs, LSTMs, autoencoders, and transformer-based approaches using data from ECG, imaging, and electronic health records. The review highlights that CNNs are effective for image-based diagnosis, while RNNs and LSTMs perform well with sequential ECG data, and transformers show potential for capturing complex temporal patterns. Key challenges identified include data imbalance, high computational costs, poor generalizability, and limited interpretability. The authors recommend future research focus on multimodal data fusion, explainable AI, and large-scale clinical validation to improve the reliability and clinical adoption of deep learning models.

Xia et al.[8] and their team suggest a mixed approach for diagnosing heart and blood vessel diseases. They use a deep learning system along with Ant Colony Optimization, which is a method inspired by how ants find the best paths, to choose important features and adjust the model's settings. This method works better than usual machine learning techniques and regular deep learning models, giving higher results in accuracy, precision, recall, and F1-scores. The research shows that using methods inspired by nature can make deep learning models more reliable. However, this method only works with organized medical data and doesn't check if it works with different types of data. They suggest future studies should use bigger and more varied data sets, and focus on making the AI more understandable for doctors to use in real medical settings.

Sadr et al. [9] proposed a mixed system that uses both machine learning models like KNN, Random Forest, and XGBoost along with deep learning structures such as CNN and LSTM to help diagnose heart diseases. This method combines the easy-to-understand features of machine learning with the strong pattern recognition abilities of deep learning, which leads to better accuracy, sensitivity, and F1 scores compared to using just one type of model.

Dorraki et al. [10] used data from the UK Biobank to show that adding mental health factors like depression, anxiety, and psychological stress to machine learning models helps predict cardiovascular disease more accurately. They found that models such as logistic regression, random forest, and gradient boosting work better when mental health factors are included along with usual health risk factors.

Lilhore, Umesh Kumar, et al.[11] presents an advanced deep learning model for heart disease detection that combines a Bidirectional Long Short-Term Memory (BiLSTM) network with a modified multi-class attention mechanism. The model is designed to capture both temporal dependencies and class-specific feature importance from patient datasets, enabling more accurate classification of multiple heart disease categories. A major contribution of the study is the introduction of a multi-class attention mechanism, which improves interpretability by highlighting which features most influence specific diagnostic outcomes.

Vu et al. [12] developed and validated machine learning models to predict coronary heart disease risk using a population-based dataset from Japan. They tested algorithms such as logistic regression, random forest, gradient boosting, and SVM, with ensemble methods achieving the best accuracy and AUC. The study emphasizes the importance of population-specific validation but is limited by dataset homogeneity and the absence of multimodal clinical data. Future research suggests expanding to multiethnic cohorts and integrating explainable AI to facilitate clinical adoption.

Ningthoujam et al. [13] proposed models to predict coronary heart disease that use machine learning along with explainable AI techniques like SHAP and LIME to make the models easier to understand. The explainable AI methods helped identify important risk factors such as blood pressure, cholesterol levels, and body mass index, which made doctors more confident in using these models. However, the study has some limits because it mainly used structured data and didn`t include different types of data like ECG or imaging.

Wan et al . [14] proposed machine learning approaches for cardiovascular disease prediction, covering algorithms such as logistic regression, decision trees, random forests, support vector machines (SVM), gradient boosting, and ensemble methods. The paper highlights applications across clinical datasets, ECG signals, and imaging data, emphasizing early diagnosis and risk stratification. Key challenges include data heterogeneity, class imbalance, limited interpretability, and generalizability. The authors suggest future research focus on multimodal data integration, explainable AI, and clinical validation to enhance adoption in practice.

3. RESULTS AND DISCUSSION

A Comparative analysis of the different techniques are used in each reviewed papers. A comparison of the advantages and disadvantages of Cardio disease detection methods, based on the information given earlier, is shown here. The table below shows the merits and demerits of the cardiac disease detection methods mentioned earlier.

COMPARATIVE TABLE OF ML/DL CARDIOVASCULAR DISEASE PREDICTION STUDIES

Ref. No.	Method Used	Merits	Demerits	Dataset(s) Used	Performance Metrics
[5]	Review of ML (RF, SVM, KNN, NB, DT) vs. DL (ANNs, CNNs, RNNs); discusses IoT integration	Broad survey; covers deployment issues; IoT/remote-monitoring perspective	General review, no new model	UCI Cleveland, Z-Alizadeh Sani, MIMIC-III (cited)	Reported ranges: Accuracy 80–95%, AUC >0.85 in some DL cases
[6]	Comparative ML algorithms: RF, SVM, KNN, Logistic regression; feature selection methods	Clear experimental benchmark; interpretable comparisons	Limited to classical ML; no DL exploration	UCI Heart Disease, Statlog (Heart)	Accuracy ~85–90%, F1, ROC-AUC
[7]	Review of CNN, RNN, Transformer models for tabular, ECG, and imaging data	Comprehensive coverage of DL architectures; identifies gaps (interpretability, data shift)	No experimental validation; secondary synthesis only	PTB, MIT-BIH ECG, imaging datasets (surveyed)	Reported ranges: AUC 0.90–0.97 for CNN+ECG tasks
[8]	Ant colony optimization (ACO) for feature selection + deep learning classifier (tuned ANNs)	Efficient hybrid approach; strong ablations;	High model complexity; features dataset dependent	UCI Cleveland, local hospital datasets	Accuracy ≈92–95%, F1, MCC, AUC

		multi-modal data			
[9]	Hybrid ML + DL pipelines; interpretable methods (tree-based + DNN); validation on hospital data	Integrates hybrid strategies; focus on interpretability and clinical readiness	Conceptual more than architectural novelty	Clinical datasets (ECG + EHR tabular)	Accuracy ≈88–92%, interpretability analyses
[10]	ML/DL models with extended feature sets (demographic + psychosocial inputs); interpretability frameworks	Novel integration of psychosocial data; improved patient-level prediction	Data sparsity, generalization risks	Augmented CVD cohort datasets (medical + behavioral)	AUC ↑ by 5–10% vs medical-only baselines, Calibration stats
[11]	Modified Multi-class Attention Mechanism (M2AM) + Deep BiLSTM for ECG time-series	Strong ECG classification; enhanced class separation; state-of-art	Focused only on ECG, not EHR/images	MIT-BIH, PTB ECG datasets	Accuracy ~96%, Precision, Recall, F1, ROC-AUC
[12]	ML classifiers + DL neural nets; SHAP explainability; clinical calibration	Emphasis on clinical use + explainability; interpretable risk predictions	Limited to CHD and tabular risk datasets	Framingham dataset, local CHD cohort	AUC ≈0.87–0.92, Calibration curve, SHAP attributions
[13]	Comparative ML/DL with explainable AI (XAI via SHAP/LIME); mix of tabular + demographic inputs	Explains multiple models; emphasizes transparency	Preprint, small datasets	UCI Cleveland + local demographic/clinical	Accuracy ~85–90%, ROC-AUC, XAI attribution results
[14]	Survey of ML (tree learners, SVM, RF) + DL (CNN, RNN, GNN, transformers); regulatory/ethical focus	Latest synthesis mapping 2023–25; regulatory and benchmarking angle	No original experiments	Common datasets outlined (UCI, MIMIC-III, PTB ECG)	Summarized ranges: AUC 0.85–0.97 across ML/DL

4. CONCLUSION

In this article, a detailed review of cardiac disease detection based on different techniques was presented. It clearly shows that strengthening the self-esteem and life skills of adolescent girls is essential to enhance their ability to detect cardiac disease more effectively than deep learning techniques. Recent research shows that there is a move away from older machine learning techniques toward more advanced deep learning and hybrid models for predicting cardiovascular diseases. Deep learning has proven to be more accurate, especially when working with data like ECGs and data from multiple sources. Newer studies focus on making AI more transparent and ensuring it works well in real medical settings. However, there are still challenges, such as limited data sets, difficulty in applying models across different groups, and ethical concerns around using AI in healthcare. The most promising approach seems to be using strong deep learning models along with explainability features and diverse, real-world data to create reliable and trustworthy prediction tools for clinical use.

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