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A Comparative Study: Prediction of Heart Disease During Stress Testing Device Based on Machine Learning and Artificial Techniques

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ABSTRACT: The heart is the most important organ in the human body. Given the dynamic nature of cardiac function under stress, predicting heart failure during physical exertion is a major challenge in clinical practice. Machine learning (ML) provides a transformative approach for analyzing complex physiological and clinical data and achieving accurate and timely predictions. This study aims to review the findings of previous studies on the use of AI in heart disease diagnosis. Several machine learning algorithms, including random forests, support vector machines (SVMs), deep neural networks (DNNs), and others, were evaluated to determine their predictive performance. The results showed that deep neural networks outperformed other models, achieving 92% accuracy and 94% sensitivity. Their ability to adapt to generally nonlinear patterns also demonstrate the importance of some features over others, such as cholesterol levels, blood pressure, chest pain, and heart rate. The study concludes by highlighting the importance of AI in supporting and assisting medical professionals, particularly in the field of heart health, which can advance beyond diagnosis and prediction.

KEYWORDS: Heart Failure Prediction,machine learning, DNN,SVM, Heart Stress.

INTRODUCTION

Heart failure (HF) is a disease that affects the heart for several reasons, leading to its inability to perform its function and pump blood as required, affecting the oxygen supply to tissues. It is caused by heart defects or problems with the heart valves, making it somewhat difficult to diagnose easily [1]. Statistics indicate that 64 million people worldwide suffer from heart problems, and the situation is increasing due to the increase in risk factors such as high blood pressure, diabetes, and ischemic heart disease, as well as a result of aging [2]. The global burden of heart failure continues to increase with rapid advances in treatments and medical devices and the need for early detection and accurate treatment remains [3].

It is worth noting that it is difficult to diagnose heart failure due to exercise specifically, as symptoms generally appear during physical activity and increase with hyperactivity of the heart. Furthermore, symptoms such as fatigue, chest pain, shortness of breath, or even angina pectoris can be similar, complicating the diagnosis. [4] In general, echocardiography and cardiac stress testing are considered diagnostic aids, but they require interpretation and expert consultation and may not reveal subtle, fundamental changes. [5] We can say that modern technologies in the field of artificial intelligence have brought about developments and a shift in terms of supporting healthcare, as they have succeeded in analyzing complex data and their ability to absorb multiple inputs and produce high-quality results, which meets the individual's aspirations for trust and reliance on them. [6]Similarly, random forest models have been shown to effectively identify key predictors such as heart rate variability (HRV), systolic blood pressure, and exercise duration, providing interpretable results for clinical use [7].

Using the SVM algorithm enables the user to monitor the heart during operation, which strengthens diagnosis by identifying nonlinear relationships and strategic patterns. [8] ML is not only concerned with increasing diagnostic accuracy, but also enables early rescue and classifies risk types simultaneously, providing a real-time assessment of the patient's condition based on data generated by wearing the necessary monitoring devices. [9] due to its high flexibility, machine learning enables stakeholders and specialists to reduce risks and detect heart problems early. It also enables the development of treatment plans with access to new data. [10] Machine learning has revolutionized the transition from immediate care to pre-care, enabling physicians or stakeholders to identify the risk of injury during stress, which can facilitate real-time intervention, helping to reduce hospital admissions and thus reduce patient volume and the likelihood of readmission and hospitalization [11]. It can also be argued that healthcare providers, based on physiological foundations, can make predictions thanks to the interpretable insights of machine learning models about the importance of parameters such as oxygen uptake or heart rate, increasing confidence in such advanced technologies [12].A healthy heart is of normal size and shape, with the heart muscle having a regular thickness and even distribution, and its bright red color reflects normal blood flow and good health. The blood vessels appear clear and pure, indicating smooth blood flow without obstructions, and the heart tissue appears smooth and free of any defects or damage. A failing heart appears abnormally large, either enlarged due to stress or shrunken due to damage, with changes in the thickness of the heart muscle walls depending on the type of failure (systolic or diastolic). Its pale, grayish, or brown color indicates poor oxygenation or tissue fibrosis. The blood vessels also appear narrowed, with signs of fluid accumulation and possibly stress, and there is fibrosis in the heart tissue. Anatomical differences include noticeable changes in the size, shape, color, texture, and thickness of the heart muscle (***Fig 1***).

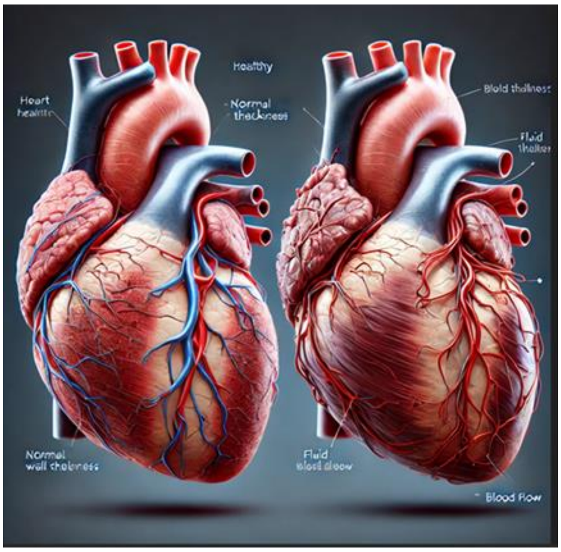

Fig 1: Healthy heart vs. heart with heart failure

LITERATURE REVIEW

In this section of the paper, we provide a brief overview of the most important research that has addressed the integration of cardiac data with artificial intelligence.

In 2015, K. Vimbandasamy, R. Sasipriya, and E. Deepa developed a machine learning model using the Naive Bayes algorithm to diagnose heart disease and support specialists in making the right, timely decisions. The algorithm achieved an accuracy rate of 86 to 90%, demonstrating the algorithm's accuracy. It used patient data that included several well-known variables that affect heart health, such as age, blood cholesterol levels, blood pressure, blood sugar, smoking, and heart rate. The study recommended expanding and expanding research to include the integration of algorithms or the adoption of other algorithms to increase diagnostic accuracy.[13]

In 2016, E. Choi et al. used recurrent neural networks (RNNs) to analyze data from medical records to predict heart failure. They used data from more than 50,000 people, including previous diagnoses, medications used, and medical procedures performed. The model achieved an accuracy of 89%. The study highlighted the importance of machine learning in supporting healthcare workers in making accurate and rapid decisions. [14]

In 2017, O. Oktay et al. developed a model based on anatomically constrained convolutional neural networks (ACNNs) to upscale 150 cardiac MRI images. They achieved 92% accuracy using advanced analysis points and were equipped with graphics processing units (GPUs), which reduced training time and increased efficiency to improve the quality and accuracy of cardiac image segmentation.[15]

In 2017, E. Choi et al. focused on early detection of heart failure using recurrent neural networks (RNNs) using data from 50,000 patients based on the patient's medical history, medications, and diagnosis. They achieved an accuracy of 88%, which improves early diagnosis of the disease.[16]

In 2017, S. F. Weng et al. developed a model to predict cardiovascular disease risk using data from nearly 3,000 patients, including patient information on age, body mass index, cholesterol levels, and other factors. They used random forest algorithms, machine learning, support vector algorithms, and logistic regression. The algorithm demonstrated an accuracy of 87%. The researcher urges the use of machine learning techniques to quickly predict heart problems, which may avoid risks to human life. [17]

In 2019, M. H. Al-Mallah and others presented a study aimed at predicting the likelihood of heart failure patients being readmitted to the hospital by analyzing clinical data from nearly 2,000 people, including age, cholesterol levels, and so on, using a random forest algorithm, support vector model, and logistic regression. The random forest model achieved a prediction rate of 83%. [18]

In the same year, M. S. Amin and others used several machine learning methods to predict heart failure using the same clinical data, including age, blood pressure, and cholesterol levels, which included 500 patients. They used the naive Bayes algorithm, random forests, and support vector machines (SVMs). They achieved an accuracy of 85%, with the random forest model outperforming the others. The study emphasizes the importance of machine learning in assisting in making clinical decisions at high speed and providing accurate and realistic solutions for evaluating health data.[19] In 2019, Z. I. Attia et al. presented an AI-based model for evaluating electrocardiograms (ECGs) to identify left ventricular dysfunction. Over 150,000 ECGs from various medical facilities were included in the cohort. Patterns associated with impaired left ventricular function were discovered using deep neural networks. The model achieved exceptional performance in early detection, with a prediction accuracy of 92%. To conduct large-scale data analysis, Google Cloud graphics processing units (GPUs) and tensor processing units (TPUs) were used to train the model. According to the study, this method may help in early detection of heart disease and reduce healthcare costs.[20]

n 2019, S.R. Tithi, A. Akter, V. Alim, and A. Chakraborty designed a model to detect interference or abnormalities in electrocardiogram (ECG) reports. They analyzed 452 samples. The data was classified into normal and abnormal, and algorithms such as nearest neighbor, decision tree, logistic regression, naive Bayes, support vector machine, and artificial neural network were applied. The data was divided into training and testing to diagnose several diseases, including coronary artery disease, proximal and minor angina syndromes, myocardial infarction, and stroke. The support vector machine achieved the highest accuracy rate of 78% [21].

In 2020, Dr. Chico and J. Gorman focused on how machine learning can be used to detect and predict survival in heart failure patients using serum creatinine levels and left ventricular ejection fraction, achieving high prediction accuracy and simplifying the complexity of the data.. The researchers employed a random forest algorithm to analyze a dataset of 299 patients, which included 13 different clinical features. The model achieved an accuracy of 87%, reflecting its efficiency in making precise predictions with only a limited set of features. The analysis and predictive modeling were conducted on high-performance servers. Here, the importance of simplifying clinical data analysis using machine learning emerges, enabling accurate medical decision-making.[22]

In 2021, O. Akbilgic, L. Butler, I. Karabayir, P. P. Chang, and others presented a study evaluating the importance and significance of electrocardiogram (ECG) in predicting heart failure (HF) and comparing the accuracy of artificial intelligence (AI) models with known risk scores such as the Framingham Heart Score (FHS) and the Atherosclerosis Risk in Communities (ARIC) scores. The researchers used data from the ARIC study, excluding participants already suffering from chronic heart failure. Using convolutional neural networks (CNNs), standard 12-lead ECG data was used to evaluate the algorithm's performance.

The study sample consisted of 14,613 participants, 45% of whom were male. ECG data were collected using a MAC PC10, and clinical data included age, sex, and other common risk factors for HF. The AI-based ECG model achieved an area under the curve (AUC) of 0.756. In comparison, the ARIC and FHS risk calculators achieved an AUC of 0.802 and 0.780, respectively. When the ECG model outputs were combined with clinical variables in an integrated model, the AUC improved to 0.818. The AI ECG model, based solely on ECG information, demonstrated predictive accuracy comparable to traditional risk calculators such as ARIC and FHS. This model holds promise for the development of early screening tools for heart failure.[23]In same year, Ahmed S. Fahmy, Ethan J. Rowen, et al. analyzed data on 1,427 patients diagnosed with hypertrophic cardiomyopathy (HCM) over a 3-year period. 283 patients (20% of the cohort) developed advanced heart failure features The study used a variety of data to train a machine learning model, including clinical data, MRI, and ECG data, using a random forest algorithm and progressive boosting. The random forest achieved an accuracy of 78%. The model identified several factors, including the extent of left ventricular hypertrophy, wall thickness, and blood flow, to predict disease stages[24].

In year 2022, Y. Haque, R. S. Zawad, C. S. A. Rony, H. Al Banna, T. Ghosh, M. S. Kaiser, and M. Mahmud, analyzeed heart rate variability (HRV) using artificial intelligence techniques to predict stress levels in individuals. HRV data were collected from various sources, including electrocardiogram (ECG) devices and wearable devices like Fitbit, Apple Watch, and specialized sensors such as Polar H10. The data included both short-term and long-term signals and underwent preprocessing to remove noise and correct missing values. Using several algorithms such as decision trees, logistic regression, deep neural networks, and support vector machines, deep neural networks outperformed other models with an accuracy of up to 92%.[25]

In 2022, A. Rath, D. Mishra, G. Panda, and S. C. Satapathy presented a deep learning model using ECG data for heart disease detection. They characterized the increase in data number and sampling frequency. The data was cleaned by extracting basic features such as QRS wavelength and patient's heart rate and using convolutional neural networks (CNNs) to improve performance. The data was analyzed using TensorFlow and Keras libraries and achieved 95% accuracy and robust classification of rare cases [26].

In 2022, Zhuojian Sun, Wei Dong, and others conducted a study to evaluate machine learning models in predicting heart failure-related mortality and hospital readmissions. They reviewed and analyzed studies from 2011 to 2021.. A total of 202 studies on statistical models and 78 studies on machine learning models were included. The statistical models primarily involved linear approaches such as logistic regression and Cox models, while machine learning models included algorithms like Random Forest, Support Vector Machines (SVM), and Neural Networks. Results showed that for mortality prediction, machine learning models achieved a higher mean c-index of 0.777 (95% CI: 0.752–0.803) compared to statistical models with a c-index of 0.733 (95% CI: 0.724–0.742). However, for hospital readmission prediction, statistical models had a mean c-index of 0.678 (95% CI: 0.651–0.706), slightly outperforming machine learning models with a c-index of 0.660 (95% CI: 0.633–0.686). Despite the promising potential of machine learning models, the study found no consistent advantage over traditional statistical models, particularly due to challenges in reliability and practical implementation. The findings emphasize that statistical models remain effective tools in clinical practice, while further research is needed to optimize machine learning models for broader applicability and improved performance in heart failure prediction.[27].

In 2023, Sangeeta Singhal used predictive analytics techniques using machine learning to predict congestive heart failure (CHF). The data included clinical and personal information for 10,000 people, including age, gender, medical history of chronic diseases (such as hypertension, diabetes, and other heart conditions), vital signs such as blood pressure, heart rate, and cholesterol levels, as well as laboratory results and certain imaging data. The goal was to identify the most influential variables in predicting heart failure. Several machine learning algorithms were tested, including decision trees, support vector machines (SVMs), and random forests. The random forest algorithm performed best, achieving 86% accuracy. The results showed that the algorithm provides early warnings for patients at risk of congestive heart failure, which enhances early intervention and tailored medical treatment for each patient. [28]

In 2024, Dr. H. Barzilai, E. Zimlichman, and others evaluated machine learning models to improve the interpretation of treadmill stress tests, such as treadmill ECG and dobutamine stress imaging, to confirm the diagnosis of coronary artery disease. Seven studies were evaluated from 2001 to 2023 using common medical datasets, such as the Online Medical Literature Retrieval and Analysis System, Web of Science, and the Cochrane Library. The results revealed that machine learning models significantly improved the sensitivity and accuracy of treadmill ECG, with sensitivity and accuracy rates exceeding 96% in some models. False positive rates were also reduced by up to 21%.. For dobutamine stress imaging, the models showed a noticeable improvement in diagnostic accuracy, with some achieving an accuracy of 92.7% and a sensitivity of 84.4%. Furthermore, natural language processing (NLP) applications achieved a remarkable 98% accuracy in classifying dobutamine imaging reports.

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Despite these promising results, the study notes that most of the analyzed studies were retrospective and small in scale. Nuclear stress tests were excluded due to the well-established clarity of previous research in this area. In conclusion, this study demonstrates that machine learning technologies hold significant potential for improving the assessment of cardiac stress tests and diagnosing coronary artery disease. However, further development and future studies are needed to expand their use and Methodology

Methodology

Dataset

The above research used multiple datasets, totaling approximately 1,000 diagnosed cases. This dataset included several variables, most notably age, gender, cholesterol level, electrocardiogram, heart rate, blood sugar level, etc.

These variables are essential for diagnosis due to their connection to heart health and their impact on its function and performance. Most of them were taken as digital data for ease of processing by the algorithms used in machine learning.

From the various studies above, we present the most prominent algorithms used to obtain the results.

MATERIALS AND METHODS

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Random Forest:

One of the most prominent and best algorithms used when data is diverse, it is often the most accurate for such studies, as it possesses advantages such as facilitating complexities in the data, as most of this data has indirect relationships with several variables. Performance accuracy in these studies using Random Forest ranged from 83 to 95%.

Deep Neural Networks:

Also used in several studies, it achieved an accuracy of 92%, enhancing the model's ability to handle large data sets.

Support Vector Machines:

It has also been used in several studies and demonstrated its accuracy in electrocardiogram data, but it is less accurate than the algorithms above, ranging from 78 to 88%.

Logistic Regression:

Overall, its accuracy was lower than mentioned, ranging from 75 to 85%, as it performs better in direct linear relationships than in relatively unbalanced data.

Convolutional Neural Networks:

This algorithm has demonstrated its superiority in analyzing image data, as it consists of multiple layers to distinguish data, and achieved an accuracy of 95%, as in the 2022 study by Reth et al.

RESULTS AND DISCUSSION

One of the most significant findings is the study conducted by Dr. H. Barzilay, E. Zimlichman, M. Cohen-Sheli, V. Sorin, E. Masalha, T. G. Allison, and E. Klang on the application of machine learning to stress echocardiography. This achieved high accuracy, highlighting the need for advanced AI techniques to support the healthcare sector. Below is a flowchart illustrating the process of using machine learning to interpret stress echocardiography. It begins with acquiring data sources, then the datasets undergo feature extraction to extract key indicators and patterns. The model is then trained on the extracted features to enhance diagnostic accuracy. The culmination of this process is the model's ability to predict cardiac outcomes with greater accuracy and understanding. CAD (coronary artery disease), CNN (convolutional neural networks); Electronic health record (EHR), global longitudinal stress (GLS), stress electrocardiography (ECG), stress echocardiography (ECHO), left ventricular ejection fraction (LVEF) and extreme gradient boosting (XGboost).[29]

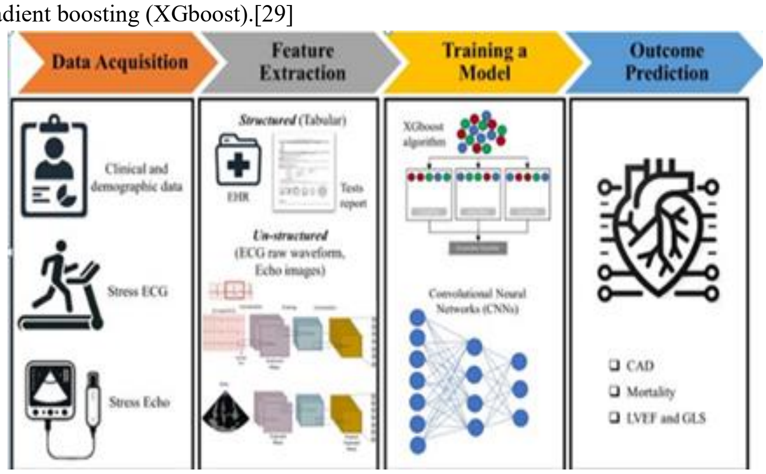

Figure 2: General structure of the diagnostic model

In a study by S. F. Weng et al., which compared random trees, logistic regression, aerobic reinforcement, and neural networks with algorithms traditionally used in medicine that have performed well in several other studies and included a wide variety of patient data on which the results were based, the ACC/AHA risk model was used as the baseline for comparison (AUC 0.728, 95% confidence interval 0.723–0.735). All tested machine learning algorithms achieved statistically significant improvements in variances compared to the baseline models (from 1.7% for random forest algorithms to 3.6% for neural networks). **Error! Reference source not found.**

Compared to the established AHA/ACC risk prediction algorithm, we found that all tested machine learning algorithms performed better at identifying individuals who may or may not develop cardiovascular disease. Unlike established risk prediction methods, the machine learning methods used were not limited to a small set of risk factors, but included more pre-existing medical conditions. Neural networks performed best, improving their prediction accuracy by 3.6%. This is an encouraging step forward. For example, the recent addition of emerging biochemical risk factors, such as high-sensitivity C-reactive protein, resulted in less than a 1% improvement in cardiovascular risk prediction [17].

Algorithms	AUC c-statistic	Standard Error*	95% Confidence Interval		Absolute Change from Baseline
			LCL	UCL	
BL: ACC/AHA	0.728	0.002	0.723	0.735	—
ML: Random Forest	0.745	0.003	0.739	0.750	+1.7%
ML: Logistic Regression	0.760	0.003	0.755	0.766	+3.2%
ML: Gradient Boosting Machines	0.761	0.002	0.755	0.766	+3.3%
ML: Neural Networks	0.764	0.002	0.759	0.769	+3.6%

*Standard error estimated by jack-knife procedure [30]

Figure 2: Comparison of different algorithms for performance evaluation using AUC and relative change compared to baseline

The graph compares the accuracy of models using artificial intelligence and machine learning techniques to predict and diagnose heart disease. The vertical section represents the study and the year in which it was conducted, while the horizontal section shows the percentage of accuracy obtained from the algorithm used. We note the evolution of studies over time.

CONCLUSION

In this study we highlight the use of machine learning and artificial intelligence to predict and diagnose heart disease. As mentioned above, previous studies have demonstrated the potential of machine learning to achieve high prediction accuracy rates. Deep neural networks (DNNs) have emerged, achieving an accuracy rate exceeding 90% when predicting heart failure during stress. This is due to their ability to detect and analyze nonlinear data in the input data. We also illustrate how diagnostic methods have evolved from the simplest to the most complex, such as the Naive Bayes model and the Random Forest model, to advanced models such as Convolutional Neural Networks (CNNs), which have excelled at classifying the most complex cases. We do not deny that there are still challenges that hinder achieving ultimate accuracy, such as data imbalance, especially in rare, special cases. These challenges have been mitigated by increasing the number of samples. The focus of this research reflects the importance of integrating machine learning systems with electronic health records, data validity and accuracy, overcoming challenges related to case interpretation, and also Commitment to maintaining patient privacy is a professional and ethical duty that cannot be ignored.

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