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ARTICLE ORIGINAL

Predicting Cardiovascular Diseases using Neural Networks: Validation with SCORE2 Risk Assessment Tool

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Summary

Introduction : This study introduces an approach to predicting cardiovascular diseases (CVDs) by leveraging neural networks and evaluates its performance against the widely recognized SCORE2 risk assessment tool. Given the significant global health impact of CVDs, our research aims to assess the effectiveness of deep learning-based models compared to traditional methods. Our methodology involves developing and deploying a neural network model capable of learning intricate patterns and relationships from a comprehensive dataset. Leveraging a large population cohort with extended follow-up enables precise and long-term risk estimation. We utilize the T-paired test to compare risk predictions between our neural network model and the SCORE2 tool. Our results indicate a notable accuracy of 0.77 for our neural network-based model in predicting CVDs, with the T-paired test revealing no significant variations in risk levels between the two methods. These findings underscore the effectiveness of neural networks as a robust tool for CVD risk prediction and advocate for further exploration and integration of these technologies to enhance cardiovascular risk assessment, thereby advancing predictive modeling in healthcare.

Keywords

Cardiovascular diseases, neural networks, SCORE2, risk assessment tool, accuracy, risk prediction

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INTRODUCTION

Cardiovascular diseases (CVDs) impose a significant global health burden, contributing to high mortality rates and diminished quality of life. Despite advancements in risk assessment tools like the widely used SCORE2 tool, the complexities of CVD risk remain inadequately addressed. These traditional methodologies often rely on predetermined risk factors, which, while valuable, fail to capture the multifaceted nature of CVD risk. Factors such as demographic information, lifestyle habits, and medical history interact in intricate ways to influence an individual's risk profile, yet current methods overlook these complexities, resulting in suboptimal risk assessments [1,2].

In response to these limitations, there has been a growing interest in leveraging machine learning techniques, particularly neural networks, to enhance CVD risk prediction. Neural networks offer the capacity to learn intricate patterns and relationships from extensive datasets, potentially offering more accurate risk assessments than traditional methods. However, despite the promise of neural networks, their application in healthcare, particularly in CVD risk assessment, requires further exploration and validation.

This research aims to bridge this gap by developing and validating neural network models for predicting CVD risk. By harnessing comprehensive datasets encompassing a wide array of risk factors, we seek to transcend the limitations of existing approaches and provide a more nuanced understanding of the predictive factors associated with CVD. Through meticulous validation against established methodologies like the SCORE2 tool, we aim to demonstrate the efficacy of neural networks in enhancing CVD risk assessment accuracy [3].

Ultimately, this research holds significant implications for clinical practice, offering the potential for more personalized and effective interventions in managing CVD. By elucidating the strengths and limitations of neural networks compared to traditional methods, we aim to pave the way for their integration into routine clinical decision-making, ultimately improving patient outcomes and alleviating the burden of CVD on individuals and healthcare systems.

This article is structured into six sections to provide a comprehensive analysis of predicting cardiovascular diseases using neural networks and validating the results using the SCORE2. It begins by defining the problem

statement and study purpose, focusing on the dataset and data mining methods used. The fourth section discusses the neural network model used for predicting heart illnesses, highlighting its ability to learn complex patterns and relationships from data. The fifth section presents a comparative analysis of the results obtained from the neural network model and the SCORE2 risk assessment tool, providing insights into their performance and effectiveness in predicting cardiovascular diseases. The sixth section summarizes the findings and implications, proposing future directions for further research and improvement in the field.

HEART DISEASES

Cardiovascular diseases (CVD) encompass a spectrum of conditions affecting the heart and blood vessels, posing significant health risks. These conditions, including coronary artery disease, heart attacks, strokes, and heart failure, result from a complex interplay of various risk factors. Understanding these factors is pivotal in assessing and predicting an individual's cardiovascular health.

Key contributors to CVD encompass an array of both non-modifiable and modifiable factors. Non-modifiable factors, such as age, gender, and genetic predisposition, play an essential role in shaping an individual's susceptibility to heart diseases. However, numerous modifiable risk factors are amenable to intervention and lifestyle modifications, offering avenues for prevention and management.

Modifiable risk factors, such as smoking, sedentary behavior, poor dietary choices, obesity, elevated blood pressure and cholesterol levels, diabetes, and stress, significantly increase the risk of cardiovascular diseases. To mitigate these risks, a wholesome lifestyle is crucial. Regular exercise strengthens the heart muscle, improves circulation, and helps control weight. A balanced nutrition, rich in fruits, vegetables, whole grains, and lean proteins, provides essential nutrients. Smoking cessation is essential as it increases the risk of heart attacks and strokes. Effective stress management techniques, such as mindfulness and relaxation exercises, help reduce stress hormones, reducing hypertension and inflammation. Maintaining a healthy weight is essential for overall heart health, as obesity is linked to high blood pressure, high cholesterol, and diabetes. By incorporating these lifestyle changes, individuals can proactively reduce their risk of cardiovascular diseases and optimize their heart health [4].

Early detection and intervention are paramount in addressing cardiovascular diseases. Timely diagnosis coupled with proactive lifestyle adjustments can effectively curb the progression of these conditions. Emphasizing preventive healthcare measures, promoting healthy lifestyle choices, and encouraging routine medical evaluations are pivotal steps in averting the onset and progression of cardiovascular diseases. Public health initiatives need to underscore the multifaceted nature of these risk factors, advocating widespread awareness and community-based interventions. By educating individuals on the significance of modifiable factors and empowering them with the knowledge to adopt healthier lifestyles, we can collectively reduce the burden of cardiovascular diseases within communities

RELATED WORKS

The provision of high-quality services at reasonable prices is a key concern for healthcare institutions (hospitals, medical centers). Quality service include effectively diagnosing patients and giving appropriate remedies [5].

By integrating clinical decision support with computerized patient records, it is possible to decrease medical errors, enhance patient safety, get rid of pointless practice variation, and enhance patient outcomes. The World Bank Country Group estimates for 2001 state that India's share of the global sickness burden was 25.2%, while a literature review indicates that this percentage has already increased to 46%. Over 60,000 people in India may away suddenly from arrhythmias and cardiac diseases every year, despite the significant advancements in pathological research and clinical technologies [6].

Even experienced cardiologists require the aid of an intelligent decision system to arrive at an accurate diagnosis of cardiac illness when there is confusion about the symptoms of heart disease. Waveform analysis, temporal frequency analysis, complexity measurements, Neuro Fuzzy RBF NN, and a total least square based Prony modelling method have all been used to identify cardiac disorders. However, classification accuracies were not good (only up to 79%), and classification of artificial neural network utilizing ANN with feature selection yields only 80% result, with these methodologies, and there is still room for improvement by selecting appropriate NN model [6]

Medical professionals use data mining techniques to find and predict illnesses while also giving patients the right care. Numerous studies in the literature have identified diseases including diabetes, hepatitis, cancer, heart disease, and others by using data mining approaches. Information about diseases, including photos, gene expressions, electronic health records, and therapy information, was used in all of these projects. Data mining approaches have lately been employed by several researchers to offer diagnostic alternatives for different kinds of heart diseases [7,8].

An analysis of various data mining techniques that are applicable to automated heart disease prediction systems. In order to detect heart disease effectively and efficiently, several techniques and data mining classifiers have evolved recently. These are defined in this work. The investigation's findings indicate that a neural network with eight or thirteen characteristics has achieved an approximate accuracy of eighteen percent so far. Moreover, Decision Tree has a 99.2% efficiency when paired with the Genetic Algorithm and six features [7]. The analysis of the aforementioned data demonstrates the importance of frequent inspections and more careful and effective techniques of treating cardiac conditions. For efficient dataset categorization in data mining, ANN is thus provided as a classification technique.

All of these experiments have one thing in common: the outcomes are vastly different from what doctors utilize on real patients. The most frequently used methods by doctors are ASCVD risk calculator and SCORE2, which provide results in a different calculating system (fig.1), whereas these models provide results in a binary system, which may not be very efficient for health workers, which is why our goal is to find a way to use neural networks to create a system that provides a similar result to the one used by doctors.

METHODOLOGY

Data Pre-processing: Initially, the cardiovascular disease dataset underwent rigorous pre-processing to ensure its suitability for model training. This included steps such as data cleaning, feature selection, and normalization, all performed using Python with the Scikit-Learn library.

Model Development: The predictive model was constructed using an artificial neural network (ANN) architecture implemented with TensorFlow. This neural network was structured with multiple layers, including dense and convolutional layers, enabling it to learn intricate patterns from the input data. Hyperparameter optimization was conducted to fine-tune the model's performance.

Training: Training of the ANN model was executed on a high-performance computing cluster equipped with GPUs. The TensorFlow framework facilitated distributed training, effectively utilizing available computing resources and expediting the training process.

Evaluation: Post-training, the model underwent thorough evaluation using a separate validation dataset. Evaluation metrics such as accuracy and loss were computed to gauge the model's predictive performance.

Comparison with SCORE2: In order to validate the efficacy of our neural network model, its predictions were juxtaposed with those of the SCORE2 risk assessment tool—a well-established benchmark in cardiovascular risk assessment. This comparative analysis provided insights into the model's accuracy and its alignment with existing clinical tools.

Model ANN

Artificial neural networks (ANNs) behave similarly to the human brain. Similar to how a biological neuron cell gets information and reacts, an artificial neural network (ANN) learns from data to classify and predict output. Non-linear statistical architecture is utilized to reveal complex problem-solving. An ANN structure is composed of an input layer for data, one or more hidden layers [9,10], and an output layer with several nodes that resemble neurons in the human brain.

Nodes in an ANN function as inputs to the input layer, which gathers data from the outside world and sends it to the hidden layer, because of the way neurons communicate with one another. Now that the data has been calculated, the hidden layer can identify the pattern. The term Multilayer Perceptron (MLP) refers to an ANN that has many hidden layers and back propagation; we will discuss MLPs in the paragraph that follows. When it is done processing, it delivers the categorized data to the output layer.

An activation function can be linear, sigmoid, logistic, tanh, or any other type of function that transforms an input function into an output function. Recently, artificial neural networks (ANNs) have become more and more popular. They are used in many different industries, such as voice recognition, image identification, facial recognition, and medicine. On the other hand, selecting the right ANN parameters and activation function could result in noticeably better prediction outcomes [11,12].

In this study, we harnessed the power of Artificial Neural Networks (ANNs) as the foundational architecture for our cardiovascular disease risk assessment model. ANNs, inspired by the complex interconnected structure of the human brain, are capable of learning intricate patterns and relationships from data, making them well-suited for tasks such as predictive modeling in healthcare.

Our ANN architecture comprises multiple layers, each serving a specific purpose in the data processing pipeline. The input layer acts as the gateway, receiving raw data inputs such as demographic information, clinical measurements, and lifestyle factors. These inputs are then passed through one or more hidden layers, where computations are performed to extract relevant features and patterns. The hidden layers serve as the heart of the neural network, carrying out complex calculations to transform the input data into a format that can be used for prediction. Finally, the output layer synthesizes the information processed by the hidden layers and produces risk predictions for cardiovascular disease.

Central to the success of our ANN model is the selection of appropriate activation functions. Activation functions introduce non-linearity into the neural network, allowing it to learn complex relationships between input and output variables [13]. In our model, we employed the sigmoid activation function in the output layer. This function maps the weighted sum of inputs to a value between 0 and 1, effectively transforming the output into a probability representing the likelihood of cardiovascular disease [14,15].

Mathematically, the sigmoid activation function is represented as $f(x) = \frac{1}{1+e^{-x}}$, (1), where (x) is the input to the function. This function ensures that the output of our model remains within a bounded range, making it suitable for tasks where the output represents a probability, such as risk prediction.

Furthermore, to optimize the performance of our ANN model, we employed iterative optimization techniques such as the Adam optimizer and binary cross-entropy loss function. These techniques enable the model to learn from the data and refine its predictions over successive iterations, ultimately leading to more accurate risk assessments for cardiovascular diseases.

Our ANN model represents a sophisticated approach to cardiovascular disease risk assessment, leveraging the capabilities of neural networks to learn complex patterns from data. By carefully selecting activation functions and employing optimization techniques, we have developed a powerful predictive model that can provide valuable insights into the risk factors associated with cardiovascular diseases.

Risk Calculator: SCORE2

In the realm of cardiovascular disease prevention, risk assessment and prediction tools have emerged as vital assets. These tools not only facilitate effective communication between patients and healthcare providers but also empower individuals to take proactive steps toward improving their cardiovascular health. Over the years, numerous risk prediction algorithms have been developed to forecast 10-year cardiovascular mortality or lifetime risk across diverse populations, encompassing healthy individuals, those with preexisting cardiovascular conditions, and individuals managing diabetes. Given the varying characteristics of patient cohorts, the utility of multiple algorithms tailored to distinct patient groups has become evident.

The 2016 European guideline has advocated for a stratification of cardiovascular mortality risk into specific categories—ranging from low (1%), moderate (1% to 5%), high (5% to 10%), to very high (10%) (fig1). This stratification not only aids in gauging an individual's risk but also dictates the intensity and nature of preventive treatments warranted across each risk category. The guideline further highlights the consideration of additional risk indicators, known as reclassification variables, when an individual's estimated 10-year risk closely aligns with a critical decision-making threshold. These reclassification variables, such as socioeconomic status, family history of early cardiovascular disease, body mass index, and computed tomography coronary calcium score, serve to refine risk assessment and offer nuanced insights into personalized risk evaluation [16].

The SCORE2 risk assessment tool, as a pivotal component of cardiovascular risk evaluation, functions as a reliable predictor in delineating risk categories and directing tailored preventive strategies. By leveraging a comprehensive array of risk indicators, it plays a crucial role in guiding clinical decisions and interventions, enabling healthcare practitioners to deliver more personalized and effective cardiovascular care.

SCORE2, a modern algorithm developed, trained, and verified to forecast 10-year risk of cardiovascular disease in European populations, improves the identification of those who are more likely to acquire CVD across Europe, and it's used by a majority of doctors in Morocco.

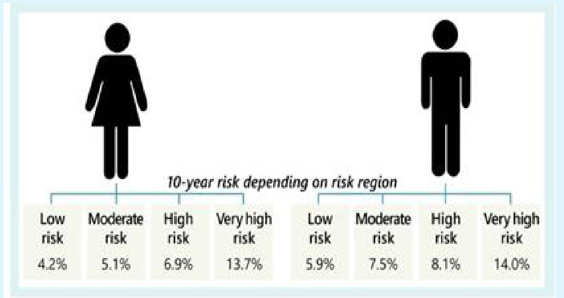

Figure 1. Scoring system of SCORE2.

Dataset

We utilized two primary datasets for our study: the Framingham Heart Study dataset and a dataset based on Moroccan patients.

The first dataset, the "Framingham Heart Study dataset," was collected from the publicly accessible component of the Framingham Heart Institute dataset.The Framingham Heart Investigation is a long-term prospective study of the causes of heart disease in people who live in the community of Framingham, Massachusetts, in the United States [17]. There are 4240 records in the accessible segment of the FHS dataset utilized in this article. The data comes from a long-term study, the research focuses on the causes and origins of cardiovascular heart disease, and it falls within one of the most effective public health disease management domains [18]. The Framingham Heart Study aimed to discover the risk factors that influence a person's health when they are diagnosed with coronary heart disease. There are 15 distinct characteristics in the dataset that impact coronary heart disease(fig.2).As an extra preprocessing step, we applied a feature selection approach based on information ranking theory to identify the most essential dataset variables. Relevant characteristics are removed throughout this variable/feature selection procedure.

The second dataset, consisting of 4034 records from Moroccan patients, encompasses various medical attributes relevant to cardiovascular health. For consistency in model testing, we retained the same set of parameters found in the Framingham dataset, as shown in the histogram (fig.3). Despite the lack of follow-up data to determine heart problem occurrences after ten years, we employed this dataset for model validation and comparison with the outcomes of SCORE2.

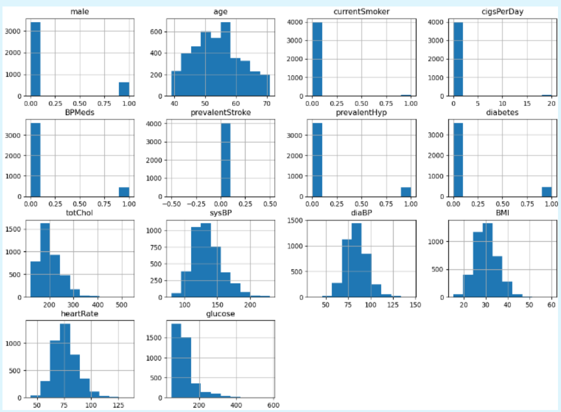

Figure 2. Histogram of the first database.

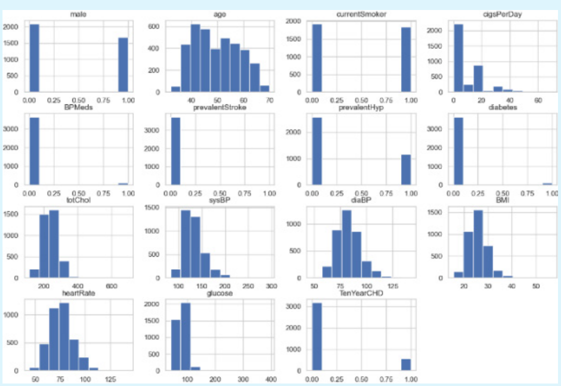

Figure 3. Histogram of the second database.

Irrelevant features are removed during this variable/feature selection procedure using a Random Forest classifier to identify the most influential predictors of cardiovascular disease risk [19]. Key factors identified included systolic blood pressure (sysBP), body mass index (BMI), total cholesterol (totChol), age, glucose levels, diastolic blood pressure, heart rate, and daily smoking. Elevated systolic blood pressure is a major risk factor for cardiovascular diseases, including heart attacks and strokes.

High BMI levels are associated with increased risk of various cardiovascular conditions, such as hypertension, coronary artery disease, and heart failure. Total cholesterol, particularly low-density lipoprotein (LDL) cholesterol, contributes to the development of atherosclerosis and increases the risk of heart disease. Age, a non-modifiable risk factor, is strongly associated with an increased risk of cardiovascular diseases, with the risk rising substantially after the age of 65.

Elevated glucose levels, indicative of impaired glucose metabolism or diabetes, significantly elevate the risk of cardiovascular complications, including heart disease and stroke. Factors such as diastolic blood pressure, heart rate, and daily smoking were also significant predictors. These insights provide valuable guidance for the predictive model, enabling prioritization of relevant predictors and refinement of risk assessment algorithms.

For enhanced visualization and interpretation, we present the feature importance analysis results using a bar plot, showcasing the relative significance of each feature in predicting cardiovascular disease risk (fig.4).

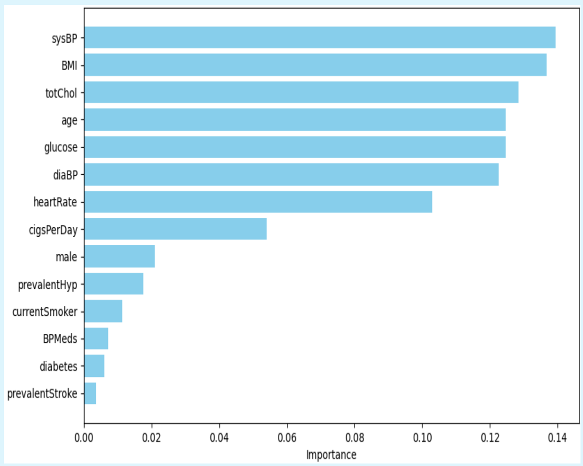

Figure 4. Feature importance in predicting cardiovascular diseases

RESULTS

Because we wanted to compare our model results to those of SCORE2, we altered the output of the neural network model from (0 or 1) to [0,1] because the risk evaluation model only returns a percentage. Due to the nature of the outcomes of both the neural network model and the SCORE2 tool being represented as probabilities, it's not feasible to calculate traditional evaluation metrics such as true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), false negative rate (FNR), the F1 score, and the Area under the ROC Curve (AUC).

Since these metrics are typically used for binary classification tasks where outcomes are dichotomous (either positive or negative), applying them to probability-based outcomes would lead to inaccuracies and misinterpretations. Instead, the evaluation of the models focused on measures such as accuracy, precision, and other relevant metrics that are suitable for assessing the performance of probabilistic models.

In essence, the nature of the outcomes being probabilities necessitates a different set of evaluation metrics that align with the continuous nature of the predictions made by both models. Therefore, while TPR, FPR, TNR, and FNR are valuable in binary classification scenarios, they are not applicable in this context where outcomes are represented as probabilities within a continuous range, as a result, we used accuracy/loss [20].

Accuracy is easier to understand. It compares the model predictions to the true values in terms of percentage to determine how well our model predicts. Loss is a value that shows the sum of our model's errors. It assesses how well (or poorly) our model is performing. If the errors are large, the loss will be large, indicating that the model did not perform well. Otherwise, the lower the value, the better our model performs.

Most of the time, we see that accuracy increases as loss decreases, but this is not always the case. Accuracy and loss are defined differently and measure different things. These two metrics seem to be inversely related, however there is no statistical relationship between them.

In the graph (fig.5) we can see that the accuracy of the model is close to 0,73 when we reach 60 epochs, in the next graph(fig.6) we tried 200 epochs and the accuracy improved to a 0,77.

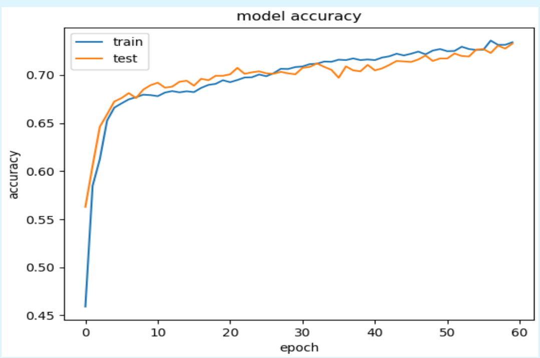

Figure 5. Model accuracy with 60epochs.

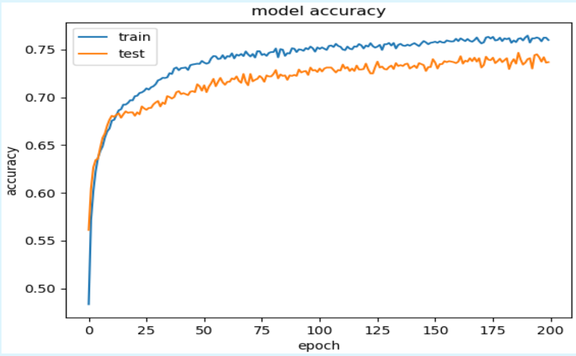

Figure 6. Model accuracy with 200epochs.

And for the model loss, a good fit model's learning curve starts out with a somewhat high training loss that steadily declines when more training instances are added, flattening out over time to show that adding more training examples has no effect on how well the model performs on training data, we can see that in this graph (fig.7) with 60 epochs and the same for the test with 200 epochs (fig.8).

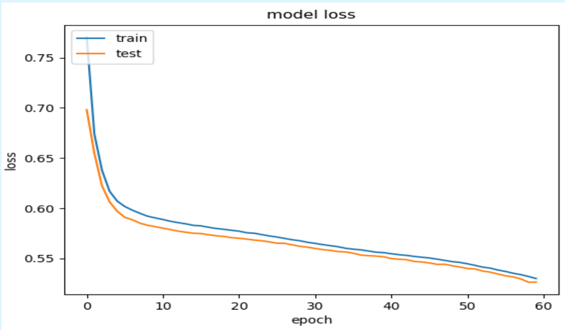

Figure 7. Model loss with 60epochs.

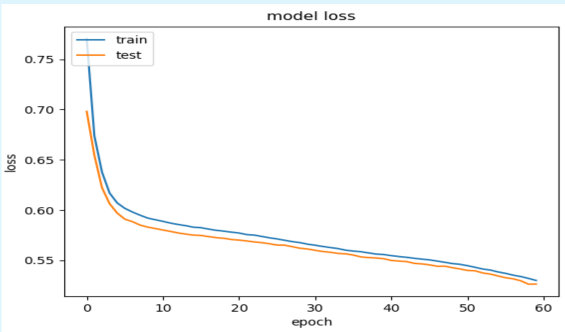

Figure 8. Model loss with 200epochs.

Upon completion of our experimental analysis and the generation of accuracy/loss metrics as depicted in the accompanying graphs, we proceeded with a meticulous comparison between our developed artificial neural network (ANN) model and the widely recognized SCORE2 risk assessment tool.

The objective was to ascertain the efficacy of our ANN model in predicting cardiovascular disease risk in comparison to the established tool. This comparison involved calculating risk scores using SCORE2 and juxtaposing them with the predictions generated by our ANN model. Employing the T-paired test, we rigorously evaluated whether any significant disparities existed in the risk levels predicted by the two methodologies.

Our analysis revealed intriguing results, indicating no statistically significant deviations in risk levels between the two approaches. Specifically, the risk estimation derived from our ANN model closely mirrored that of SCORE2, with the ANN model yielding a risk estimation of 9.17 percent, whereas SCORE2 yielded 9.03 percent ($p=0.10$) [21].

This outcome underscores the robustness and reliability of our ANN model in predicting cardiovascular disease risk, thereby highlighting its potential as a valuable clinical tool for risk assessment and decision-making.

Such comparative insights not only validate the efficacy of our approach but also contribute significantly to the ongoing discourse surrounding the integration of machine learning techniques in cardiovascular risk prediction, fostering advancements towards more informed clinical decisions and improved patient outcomes.

DISCUSSION

Limitations of the Proposed Algorithm: While our neural network-based approach shows promise in predicting cardiovascular diseases, it is essential to acknowledge its current limitations. One limitation lies in the reliance on available data and the quality of the dataset used for training. Despite efforts to pre-process the dataset rigorously, including cleaning and normalization, the presence of incomplete or noisy data may impact the model's performance and generalizability.

Interpretability and Explain ability: Another limitation of our algorithm pertains to its interpretability and explain ability. Neural networks, particularly complex architectures, are often regarded as «black-box» models, making it challenging to interpret the underlying decision-making process. As such, clinicians may find it difficult to trust and integrate the model's predictions into clinical practice without a clear understanding of how it arrives at its conclusions.

Generalizability and External Validation: Furthermore, the generalizability of our algorithm across diverse patient populations and healthcare settings remains a concern. While we conducted internal validation to assess the model's performance, external validation on independent datasets from different demographic regions and clinical contexts is imperative to ascertain its robustness and effectiveness in real-world scenarios.

Integration into Clinical Workflow: Integrating the proposed algorithm into existing clinical workflows presents practical challenges. Clinicians may require additional training to interpret and utilize the model's predictions effectively. Moreover, seamless integration with electronic health record systems and other healthcare technologies is necessary to facilitate its adoption and usability in clinical practice.

Future Directions and Mitigation Strategies: Despite these limitations, there are avenues for improvement and mitigation. Future research could focus on enhancing the interpretability of the algorithm through techniques such as feature importance analysis and model visualization. Additionally, collaborative efforts to collect diverse and high-quality datasets, along with rigorous external validation, can bolster the algorithm's generalizability and reliability.

CONCLUSION

In conclusion, our study highlights the promise of artificial neural networks (ANN) in cardiovascular disease (CVD) risk assessment. Our comparison with the established SCORE2 risk calculation system reveals encouraging alignment between the two methods. However, to further advance the field, several concrete avenues for future research merit exploration.

Firstly, enhancing the quality and completeness of data in CVD datasets is imperative to bolster algorithm performance. Additionally, incorporating additional risk factors and biomarkers into the predictive model holds potential to refine its accuracy and comprehensiveness.

Furthermore, conducting external validation studies across diverse patient populations is essential to validate the model's effectiveness and generalizability. Efforts to enhance interpretability and transparency will facilitate its seamless integration into clinical practice.

Moreover, longitudinal studies investigating the ANN model's long-term predictive capabilities and its efficacy in forecasting cardiovascular outcomes over time are warranted. By pursuing these research directions, we can deepen our understanding of CVD prediction and management, ultimately advancing patient outcomes worldwide.

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