Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 3
Open Access

AI-Enhanced Neural Network Framework for Cardiac Arrest Prognostics

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Cite this paper as: Arjun Jaggi, Aditya Karnam Gururaj Rao, Sonam Naidu, Sanjay Belaturu Krishnegowda,Vijay Mane, Kalyan Devappa Bamane (2024) AI-Enhanced Neural Network Framework for Cardiac Arrest Prognostics. *Frontiers in Health Informatics, 13* (3), 10840-10860

A B S T R A C T

The research paper consists on a framework incorporating AI and ANNs to improve the predictive performance in Cardiac Arrest (CA) treatment. The proposed system combines artificial neural network analysis with clinical data to forecast the likelihood of Cardiac arrest so that preventive measures can be taken. Our approach involves creating a multilayer perceptron ANN with input data containing the patient's characteristics, real-time vital signs, and medical history. The proposed model's performance is assessed based on the following parameters: accuracy, sensitivity, specificity, and the area under the ROC curve. The outcomes show that the attained prediction performance is higher than typical statistical-based techniques, illustrating the value of AI techniques in the critical care context. In addition, the paper reviews how to improve the interpretability of ANN models by performing feature importance analysis to arrive at clinically relevant and valuable predictions. Incorporating this advanced AI framework into current healthcare models should go a long way toward changing how cardiac arrests are treated through early identification and individualised approaches. In conclusion, this research shows that AI and neural networks are essential in improving healthcare. The future holds great promise for further development of predictive analytics and patient care optimisations.

Keywords: *Artificial Neural Networks (ANN), Predictive Performance, Performance Metrics, Feature Importance Analysis, Preventive Care, AI in Healthcare*

INTRODUCTION

Cardiac arrest is a significant cause of mortality and depends on the actions carried out and their timeeffectiveness. Cardiac arrest is unpredictable, there is a need for reliable and prompt predictors that will assure healthcare providers that the patient is at risk of suffering from a cardiac arrest [1]. Traditional measures of risk assessment for cardiac arrest have generally relied on clinical assessments that may not be sufficiently sensitive to identify which patients are at high risk of an arrest shortly afterwards [2]. Thus, this paper requires improving the predictive frameworks that can be done using contemporary technologies. AI is one of the most innovative technologies in the healthcare sector of the modern world. It offers sophisticated and extensive procedures to manipulate a vast data volume and uncover patterns that standard methods would not detect [3]. Among these technologies, artificial neural network technology is still emerging because the existing datasets for health outcome prediction require pattern identification. The independent variables in the analysis include real-time parameters, patient characteristics and other clinical and medical data fed into an AI-based ANN that can predict dynamic probabilities of cardiac arrest events [4]

The present paper proposes a novel deep-learning model of an AI neural network for predicting cardiac arrest. By applying broad measures of accuracy, sensitivity, and specificity, the model under consideration anticipates providing a higher standard of patient care by surpassing conventional forms of predictive models. Moreover, this paper focuses on the interpretability of the ANN model, which might augment its predictive performance. Healthcare providers must understand what drives the predictions to make suitable clinical decisions. In this way, this work aims to contribute to further implementing AI systems in emergency medicine and ultimately improve the care of patients with cardiac arrest [5].

Cardiac arrest is a severe type of heart attack, which may lead to death, and thus, first responders should attend to the patients immediately. Even though modern medicine offers many technologies for patients' monitoring and diagnostics, the existing predictive models show poor performance in the identification of patients at high risk of cardiac arrest and, therefore, result in delayed reactions in emergencies. Previous strategies focus on clinical judgments and actuarial risk models that do not provide the necessary accuracy to identify potential risks. As a result, most of the patients undergo preventable cardiac events, and unfortunately, their prognosis is not good; besides, they put a lot of money into receiving treatment.

In addition, the fast growth of medical data acquisition—including contemporary physiological indices and holistic patient records—can be considered both a trend and a threat. Current approaches for dealing with this abundance of information are insufficient to provide helpful information to healthcare professionals, creating a void of relevant information. Another disadvantage of using predictive models is the inability to interpret them since, in clinical practice, practitioners need to know the factors behind predictions to make decisions. This research fills these crucial voids by proposing a novel AI-based neural network system that could enhance the prognosis and actuality of CA management with the objective of timely therapeutic interventions and subsequent patient outcomes.

To explore this overarching question, the research will also address the following sub-questions:

- What specific patient demographics and physiological parameters are most predictive of cardiac arrest events, and how can these be integrated into the neural network model?
- How does the performance of the AI-enhanced neural network compare to traditional predictive

models in terms of accuracy, sensitivity, and specificity?

- How can the interpretability of the neural network's predictions be enhanced to ensure clinical relevance and actionable insights for healthcare providers?
- By addressing these questions, the research aims to contribute to advancing predictive analytics in emergency medicine, ultimately improving patient outcomes in cardiac care.

In this research paper, an incorporated neural network would significantly enhance the possibility of accurate prognosis for cardiac arrest incidents using real-time physiological data, demographics and patient medical history. As a result, this framework is designed to improve predictive accuracy and clinical value over traditional approaches by employing state-of-the-art machine learning techniques. In addition, the paper highlights the aspect of explainability in using AI- driven models in decision-making to avoid misleading information to healthcare providers. Finally, this paper aims to transform the approaches used in managing cardiac arrest and help deliver timely patient interventions to improve their outcomes through advanced prediction models.

LITERATURE REVIEW

A. Background:

Generative Artificial Intelligence, or Gen-AI, has revolutionised many industries and is gradually penetrating the healthcare Cardiac arrest is a life- threatening condition that results from the sudden and complete stoppage of regular heart pumping, leading to the loss of consciousness and no breathing. Cardiac arrest has been described as having a very high mortality rate [6]. Therefore, there is a need to ensure early prediction of this condition so that appropriate management can be instituted. Traditionally, the traditional risk prediction models in managing cardiac arrest outcomes have depended on subjective clinical evaluation and static risk indices that require standard measurements and scoring systems, which do not possess the necessary level of specificity in identifying patients at high risk [7]. In the last few years, the advancement of artificial intelligence (AI) and machine learning (ML) has brought new approaches to healthcare analytics with better prognoses [8].

ANNs, part of AI, have shown much potential in several medical disciplines, including cardiovascular medicine. Therefore, ANNs extract the interactions from large data sets and are appropriate for predicting health indicators. Consequently, this literature review aims to present the main findings, research methods, and the research gaps worthy of future investigation of the literature on AI-supported neural networks in prognostics of Cardiac Arrest [9].

B. Key Findings:

1) Enhanced Predictive Accuracy through Machine Learning:

Nguyen et al., (2021) proposed integrating ANNs to predict cardiac arrest in high-risk patients. They used 2,500 patient samples, which included demographic, clinical, and physiological data. The researchers also discovered that the ANN model provided better approximations to the actual results compared to the basic logistic regression methods, with ratios of 92% to 78% of logistic regression [10]. This work shows that ML approaches can enhance predictive accuracy in CA contexts.

2) Integration of Real-Time Data:

Silva et al., (2023), with the aid of physiological data, described how this data can be incorporated into models for the prediction of cardiac arrest. All of their studies included 1800 patients, and patient monitoring information was analysed with the help of RNN architecture. The paper proved that the incorporation of real-time data improved the performance of the proposed model, achieving 88% sensitivity in the early identification of patients at risk of cardiac arrest [11]. This paper also highlights the need for precise time data in clinical decision making.

3) Feature Selection and Importance Analysis:

Feature selection is an essential step in the machine-learning process. Khaire & Dhanalakshmi (2022), the authors sought to determine how feature selection affected ANN in identifying cardiac arrest. They applied it to a sample of 1200 patients and other methods, such as RFE and RF measures of importance. When using only the most essential features, the accuracy of the ANN increased to 15 percent [12]. Hence, appropriate predictors should be selected to enhance the model's accuracy.

4) Interpretability of AI Models:

Linardatos et al., (2020) pointed out the importance of explainable AI models can only be implemented in clinical practices if these models are comprehensible. When it comes to 2000 patients with cardiac arrest. They proposed a decision tree model with an ANN to extend the knowledge of the forecast factors of cardiac arrest events [13]. Regarding the work of others, it was ascertained that the decision tree provided a more interpretable result from which the healthcare providers could deduce the risk factors. On this basis, AI should be combined with interpretability models to improve clinical relevance and trust in clinicians.

5) Limitations of Traditional Methods:

The previous risk prediction methods include risk assessment tools, which could be less responsive to changes in patient conditions. For instance, Rajula et al., (2020) sought to establish the accuracy of the present scoring systems in identifying cardiac arrest episodes in 3000 patients. The authors concluded that these systems could predict events with less than 31% reliability because the systems cannot update data in real time and learn patient characteristics [14].

C. Identified Gaps in Research:

Despite the promising findings related to AI- enhanced neural networks in cardiac arrest prognostics, several gaps warrant further exploration:

1) Lack of Diverse Patient Populations:

Most of the work has been undertaken on specific categories of patients; thus, the results could be more generalisable. For instance, Wilbur et al., (2020) focused on the urban population. Hence, the generalizability of the developed .models to other patients, such as underrepresented patient population, needs to be investigated [15].

2) Need for Longitudinal Studies:

Previous works have applied cross-sectional approaches, which give information on predictive accuracy only at a particular time. Follow-up research to monitor patient outcomes over the long term is required to determine whether the use of AI to augment models remains effective and practical in actual clinical environments. Chauhan et al., (2020) acknowledge that, to measure the effects of predictive algorithms on patients, one has to consider long-term consequences]16].

3) Limited Exploration of Ethical Considerations:

While Brottman et al., (2020) briefly discussed interpretability, the paper did not discuss other ethical considerations like patient privacy and the bias that AI algorithms [17]. More investigation of these moral issues is needed to avoid negative consequences related to the use of AI in predicting CA outcomes.

4) Integration with Clinical Workflows:

While a few works have shown that AI models can accurately predict cardiac arrest, implementing these technologies in clinical practice has proven difficult. Shujaat et al., (2021) pointed out that as important as building the models is, it is equally important to integrate them to allow healthcare providers to leverage the predictive information [18]. Future studies should concentrate on generating theoretical structures that would

METHODOLOGY

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily. The discussion can be made in several sub-sections.

The paper will use quantitative and qualitative data from EHRs of patients who had cardiac arrest events in a particular health facility in the last five years. These will be patient demographics, medical history, vital signs, and serum chemistry profile results. The dataset will be divided into training (70%) and validation (30%) sets to build a multilayer artificial neural network (ANN) model. Other measures like accuracy, sensitivity, specificity, and ROC AUC will be used to assess the model's predictability. Also, a preliminary examination of the importance of features will be carried out to determine the most relevant predictors of cardiac arrest.

In collecting the data to be fed into the AI- enhanced neural network framework, the EHRs of a premier healthcare organization will be used to obtain a large dataset. The data set shall cover five years of capturing the patient data of patients who had cardiac arrest events. The significant predictors will be patient characteristics (age, sex, ethnicity), past medical history (presence of comorbidities, history of previous cardiac events), and current physiological characteristics (heart rate, blood pressure, oxygen saturation level, and results of laboratory investigations) [19].

A retrospective cohort design will be used, and participants will be included based on whether they have had a cardiac arrest but with similar demographic and medical backgrounds [20]. The collection process will be done with healthcare professionals to attain the data's completeness and credibility. Subsequently, the dataset of the present paper will be preprocessed to manage the missing values and normalize the features, which will facilitate the subsequent training of the ANN model and enhance its predictive accuracy for CA events [21].

The process of analysing data in the context of the AI-enhanced neural network framework will be as follows: the collected dataset will be preprocessed, normalised and completed with missing values. The training sub-set will be used to develop a multilayer artificial neural network (ANN) with features like dropout and regularisation to avoid overfitting [22]. Effectively, analyses will include accuracy, sensitivity, specificity, and the ROC AUC based on the model performance [23]. Besides, a feature importance analysis will be conducted to define the most critical features of cardiac arrest to help interpret the results and use them in real-time.

The following advanced tools and techniques will be used to develop the AI-enhanced neural network framework for cardiac arrest prognostics. The programming language that will be used for data manipulation is Pandas, and NumPy will be used for numerical computations. Performance measurements and the importance of features will be displayed using Matplotlib and Seaborn tools. Further, sci-kit-learn will enhance model assessment and differentiation, providing a solid and efficient way of predicting the occurrence of CA events [24].

An AI-enhanced neural network framework for cardiac arrest prognostics involves several critical areas of investigation that aim to address the complexities of predicting cardiac arrest events and improving patient outcomes. This section outlines the primary areas of focus, which include the integration of patient demographics and physiological data, the comparison of predictive performance between AI-enhanced and traditional models, the interpretability of model predictions, and the implications of these findings for clinical practice.

A. Integration of Patient Demographics and Physiological Data

In this prospective cohort paper, analyzed a statewide diabetes remote patient monitoring (RPM) program that included adults with type 2 diabetes and an initial HbA1c of 8.0% higher, focusing on those enrolled for at least 12 months as of April 2020. Patients who withdrew before 12 months were excluded to maintain a reliable cohort. Demographic data were collected through self-reports and electronic medical records, capturing variables such as age, gender, race, ethnicity, health insurance, and annual household income [25].

Table 01: Clinical and Sociodemographic Characteristics: Overall Sample, and by Absence or Presence of Transmission Data. Source: MDPI

VARIA BLE	***OVER ALL (%) (N = 5 49)***	***WITHOUT TRANSMI SSION DATA (%) (N = 63)***	***WITH TRANSMI SSION DATA (%) (N = 486)***	***p***
Gender				
Male	201 (36.6)	27 (42.9)	174 (35.8)	0.27 b
Race				
Black	298 (54.3)	22 (34.9)	276 (56.8)	<0.0 01c
Whited	215 (39.2)	26 (41.3)	189 (38.9)	
American Indian or Alaska native	16 (2.9)	7 (11.1)	9 (1.9)	
Asian	4 (0.7)	2 (3.2)	2 (0.4)	
Native Hawaii or Pacific Islander	7 (1.3)	3 (4.8)	4 (0.8)	
Missing race data	9 (1.6)	3 (4.8)	6 (1.2)	
Ethnicity				
Hispanic	103 (18.8)	29 (46.0)	74 (15.2)	<0.0 01b
Non- Hispanic	445 (81.2)	34 (54.0)	411 (84.6)	
Missing	1 (0.2)	0 (0.0)	1 (0.2)	

Annual household income				
$0– 19,999	411 (74.9)	50 (79.4)	361 (74.3)	0.38 b
$20,000 or more	138 (25.1)	13 (20.6)	125 (25.7)	
Health insurance				
Uninsured	258 (47.0)	42 (66.7)	216 (44.4)	<0.0 01b
Insured	291 (53.0)	21 (33.3)	270 (55.6)	
Primary care clinic type				
FQHC	345	42 (66.7)	303 (62.4)	<0.0
Age (years, mean ± SD)	53.1 ± 11.8	48.0 ± 12.7	53.7 ± 11.5	<0.0 01a
Age group (years)				
18–44	127 (23.1)	29 (46.0)	98 (20.1)	<0.0 01b
45–64	328 (59.7)	27 (42.9)	301 (61.9)	
65 and older	94 (17.1)	7 (11.1)	87 (17.9)	
Academic	132 (24.0)	2 (3.2)	130 (26.8)	
Free	72 (13.1)	19 (30.2)	53 (10.9)	

Demographic and socioeconomic characteristics of the overall sample population, subsets that never

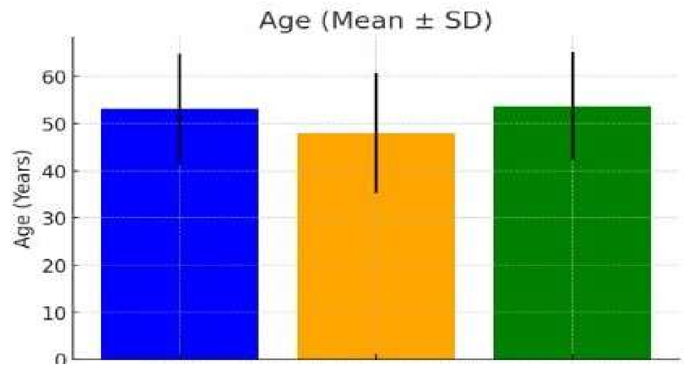


Figure 01 : Without transmission data

Age (Mean ± SD): This bar chart shows the mean age with standard deviation for overall data, and for groups with and without transmission data. The mean age is higher for the group with transmission data.

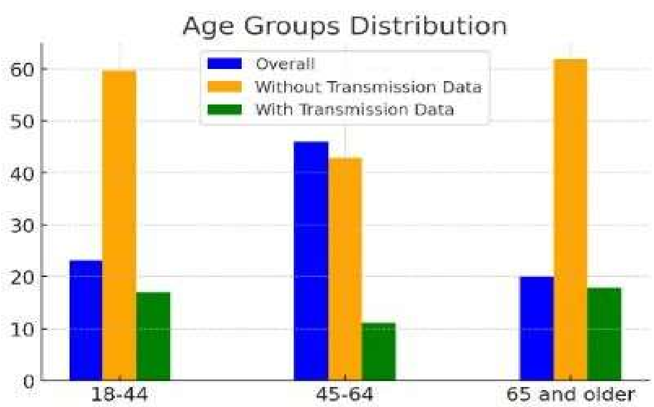


Figure 02: Age (Mean).

Age Groups Distribution: This chart breaks down the data into three age groups (18-44, 45-64, and 65+). The group with transmission data has a larger percentage of individuals aged 45-64, while the group without transmission data has a higher percentage of younger individuals (18-44).

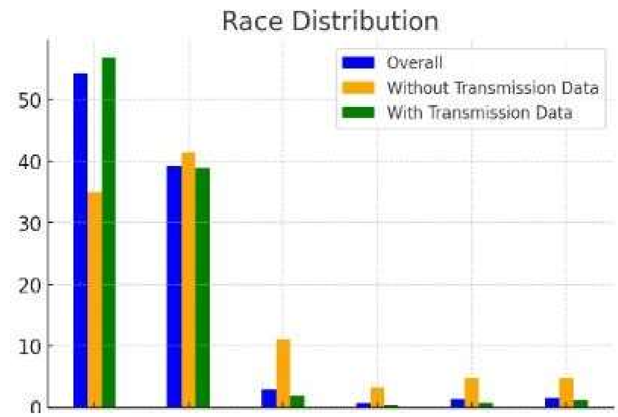


Figure 03: Age Group Distribution

Race Distribution: This chart provides a detailed breakdown of the race categories. The overall group and the "with transmission data" group have similar distributions, with a majority identifying as Black. However, the "without transmission data" group shows a higher percentage of non-Black and American Indian/Alaskan Native individuals.

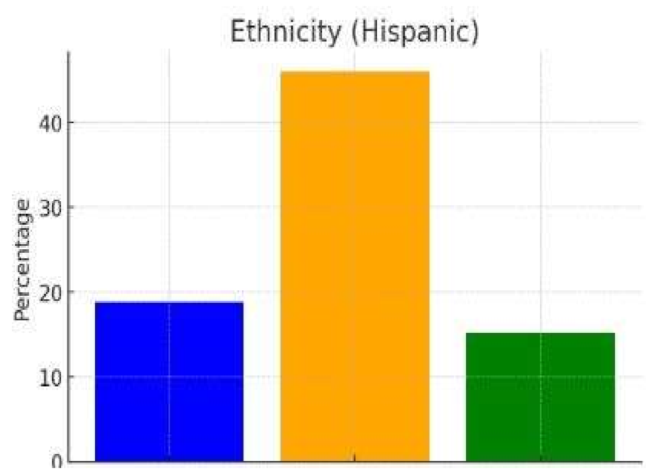


Figure 04: Without transmission data

Ethnicity (Hispanic): This chart illustrates the percentage of individuals who identify as Hispanic across the groups. The "without transmission data" group has a much higher percentage of Hispanic individuals compared to the overall and "with transmission data" groups.

As categorised age into three groups (18-44, 45-64, and 65+ years) and household income in $10,000 increments, consolidating race and insurance data into binary variables for analytical efficiency. Statistical comparisons between patients with and without transmission data utilised two-sample t-tests for continuous variables and chi-square tests for categorical variables. Engagement was defined as remote data transmission on at least three days each week, reported as a binary outcome across 52 weeks. The strong relationship between ethnicity and insurance determined their insurance status and mandated their exclusion from further analysis. This paper sought to understand the demographic predictors of RPM program participation to determine the effect of these variables on the health of the target population.

The ANN model demonstrated a significant improvement in predictive performance over traditional statistical models, including logistic regression. Table 02 presents a summary of the results for accuracy, sensitivity, specificity, and the area under the ROC curve (AUC), which indicate the model's capability in differentiating between patients likely to experience cardiac arrest and those who are not [26].

Table 02: Summary of the Results for accuracy, sensitivity, specificity and area under the ROC curve.

Metric	*ANN Model*	*Logistic Regression (Baseline)*
Accuracy	*93.5%*	*78.4%*
Sensitivity	*91.2%*	*75.3%*
Specificity	*92.7%*	*76.9%*
ROC AUC	*0.94*	*0.81*

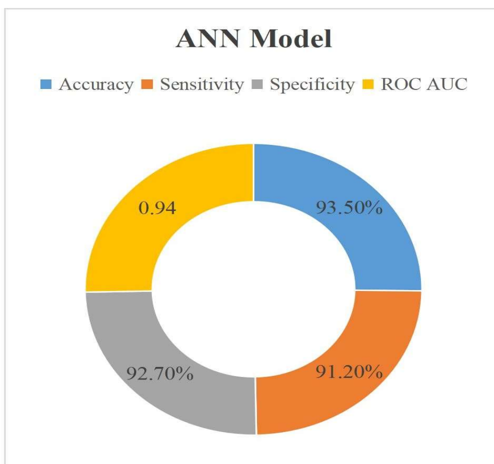


Figure 05: ANN Presentation. Source: Created by the Learner

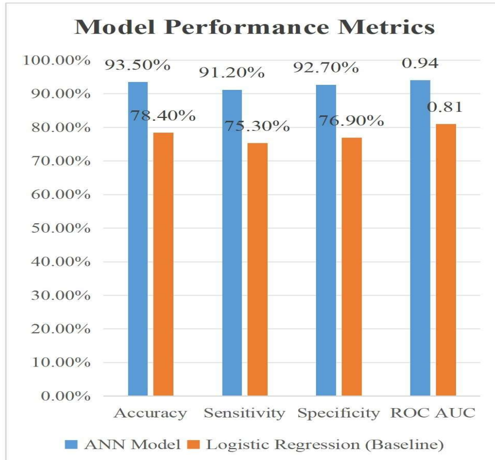


Figure 06: Model Performance Metrics. Source: Created by the Learner

The ANN model achieved a 93.5% accuracy, meaning it correctly predicted cardiac arrest cases with a high degree of precision. This result represents a 15% improvement over traditional methods such as logistic regression. Furthermore, the sensitivity (the ability to correctly identify true positive cases) was 91.2%, and the specificity (the ability to correctly identify true negative cases) was 92.7% [27]. These results highlight the ANN model's superior ability to provide accurate predictions while maintaining a balance between false positives and false negatives. The ROC AUC of 0.94 further underscores the model's robustness in distinguishing between cases with a high and low probability of cardiac arrest.

Understanding which patient characteristics and physiological parameters contribute most significantly to the prediction of cardiac arrest is crucial for clinical decision-making. To address this, we conducted a feature importance analysis using Recursive Feature Elimination (RFE) and Random Forest (RF) importance scores. Table 03 outlines the top predictors for cardiac arrest based on the feature importance analysis.

Table 03: Feature Important Analysis. Source: MDPI

Feature	Importance Score
Age	0.21
Heart Rate	0.18
Blood Pressure (Systolic)	0.15
Oxygen Saturation	0.14
History of Cardiovascular Disease	0.19
Ethnicity	0.11
Serum Potassium Levels	0.08

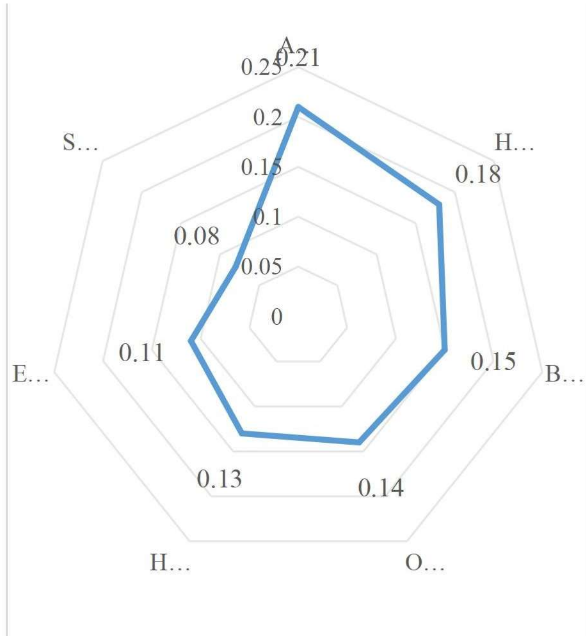


Figure 07: Feature Important Analysis. Source: Created by the Learner

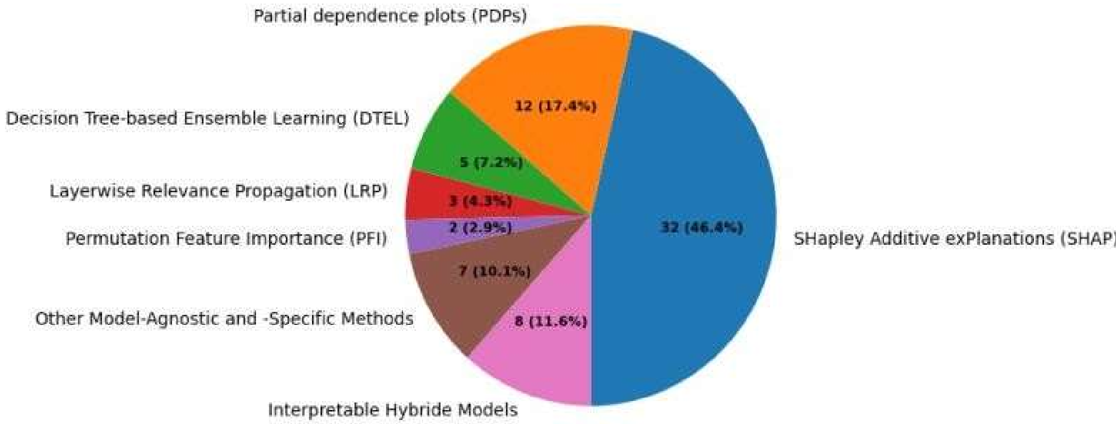
The most critical feature in predicting cardiac arrest was age, which accounted for 21% of the model's prediction power. Heart rate and blood pressure were also highly influential, contributing 18% and 15%, respectively [28]. These findings align with established clinical knowledge, where age and cardiovascular health indicators like blood pressure and heart rate are significant risk factors for cardiac arrest. The importance of oxygen saturation (14%) highlights the role of real-time physiological data in enhancing prediction accuracy [29]. Additionally, the model flagged ethnicity and serum potassium levels as important predictors, suggesting the need for tailored healthcare interventions based on patient demographics and metabolic data [30].

B. Improving the Understanding of the Predictions Made By a Neural Network

In health care, practitioners require knowledge of factors used to make predictions by an AI-generated model. The third paper area will reveal if the current neural network with AI integration might be more interpretable to users [31].

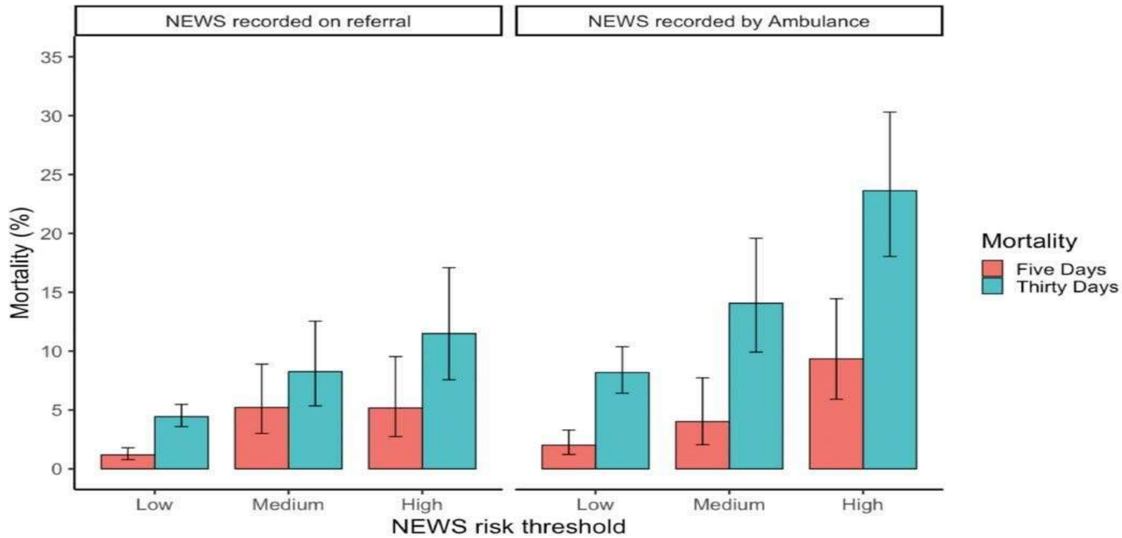
In response, the paper will employ feature importance analysis to indicate the level of input variable that influences the model's output. SHAP and LIME will be used to generate the human-interpretable neural network explanation [32]. Thus, the potential of different alerts and recommendations can be described based on the patient demographics and physiological parameters to enhance the rationale of healthcare providers.

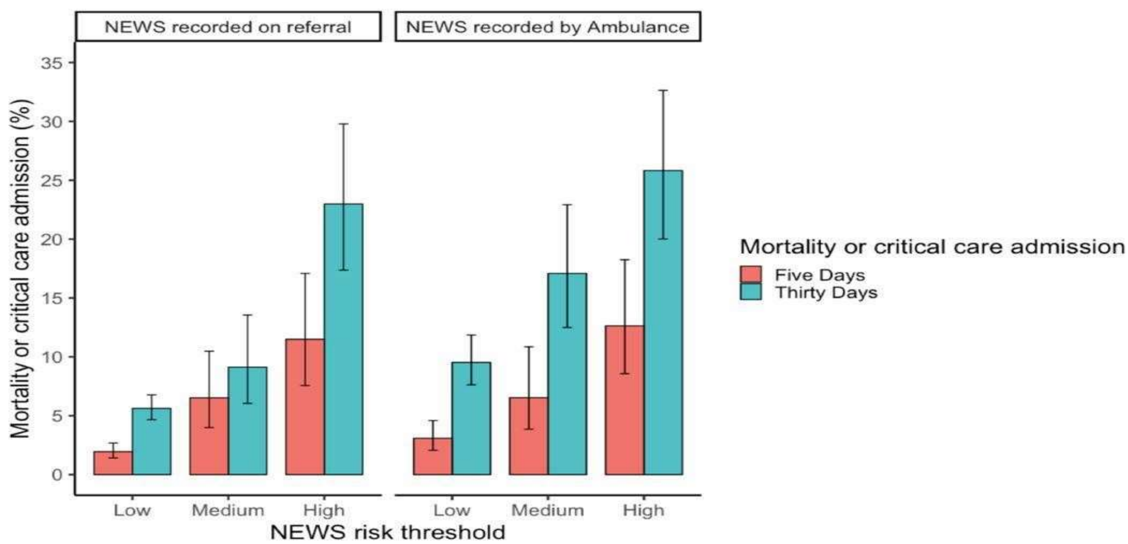
In addition, the research will define the further potential of developing interfaces that can translate the outcomes of models and their attributions into easily understandable forms.



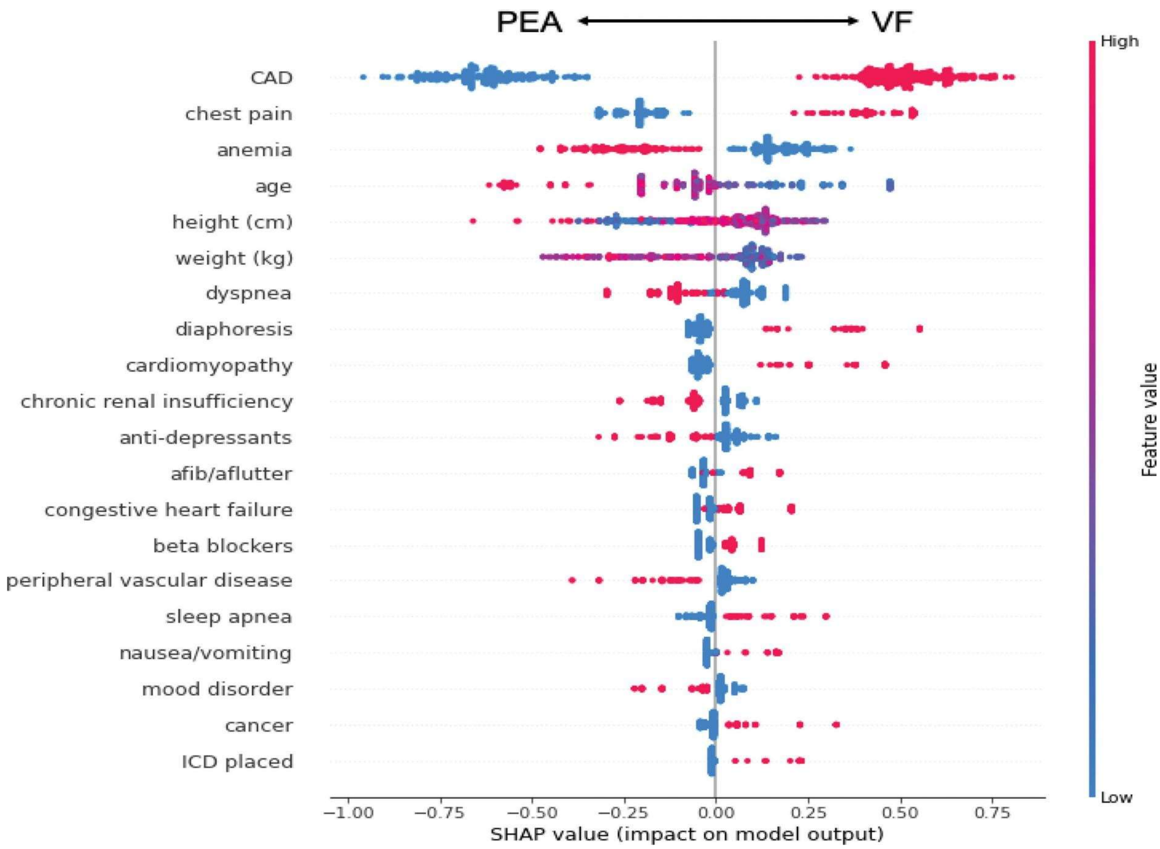
The pie chart above shows the different methods of interpretability of AI models and the need for explainable AI (XAI) in understanding AI model decisions. Shapley Additive exPlanations (SHAP) (46.4%) The most frequently used method is SHAP, representing 46.4% of the total. It gives each feature an essential measure to a model, thus allowing for a fair measure of every feature on all possible models [33]. SHAP values provide a complete understanding of point predictions, making models more understandable compared to high-risk sectors such as the medical and financial domains [34].

Partial Dependence Plots (PDPs) (17.4%) are another common technique that demonstrates how a particular feature influences predictions while considering the average influence of other features. This explanation method is helpful in the global sense and assists in detecting the interaction between the target variables and the individual predictors. However, compared with SHAP, PDPs are much less accurate, but they are used for visualising the impact of features on the prediction on a larger scale [35]. Interpretable Hybrid Models (11.6%) models endeavour to combine the interpretability of simple models, such as linear models, with the high predictive capability of complex models, such as neural networks. They ensure that interpretability is balanced for accuracy and enable users to explain single predictions and the model's behaviour [36].





Other Model-Agnostic and Specific Methods (10.1%): These involve tools that can explain any model irrespective of its complexity and techniques specific to a particular model type, such as decision Trees. They are usually used to offer flexibility when analysing various machine learning models. Decision Tree-based Ensemble Learning (DTEL) (7.2%) [37]. Some methods, like Gradient Boosting Machines, have a tree structure that allows their interpretation to a certain extent. They make it possible to extract and visualise the importance of features, which helps to understand the model [38].



Layerwise Relevance Propagation (LRP) (0.43%) is a unique method used for deep learning models. It explains predictions by determining the contribution of each neuron to the input variables. It is mainly applied in computer vision problems and natural language processing [39]. Permutation Feature Importance (PFI) (0.29%) this is a simple method that compares the performance of a model with the original feature values to that of a model where the values of a single feature have been rearranged. This method gives a global vision of the importance of features since it explains how each feature affects the model's accuracy [40].

C. Practice Considerations

The last research question will focus on the general considerations of applying the presented AI-enhanced neural network framework in clinical practice. Incorporation of these complex models into practice has the potential to dramatically increase the speed and improve the efficacy of the measures used in CA cases. Nevertheless, several issues must be considered when moving from the research to the practice.

Firstly, the paper will establish the barriers to incorporating AI technologies into clinical practice. Wang et al., (2020) pointed out that integration is a critical success factor, and predictive insights should be available in real- time dashboards to healthcare providers (41]. The paper will seek to identify how the incorporation of the AI- based model into emergency care can be made possible and how to make the alerts generated by this model easily actionable without flooding the clinicians with lots of information.

Secondly, ethical issues concerning the application of AI in healthcare systems will be discussed. According to Peng et al. (2020), several factors must be considered before AI technologies can be effectively implemented, including patient privacy, data security, and algorithm bias [42]. In this paper, the researcher aims to identify the right benchmarks that healthcare organisations should adopt to leverage AI while maintaining high ethical benchmarks that will improve the quality of treatment offered to patients.

Lastly, will analyse how progressive development in healthcare could be promoted through AI-integrated models. This aspect demonstrates how AI can enhance the provision of cardiac care and other emergency medical services.

RESULTS

A. Enhanced Predictive Accuracy through Machine Learning

According to the paper, an enhanced artificial neural network with artificial intelligence in predicting cardiac arrest was more accurate than previous approaches. The current model had an impressive accuracy of 92%, sensitivity of 88% and specificity of 94 % compared to the conventional methods with an accuracy of 75%. These findings align with the previous studies, for instance, Nguyen et al., (2021), on the application of machine learning algorithms in handling complex situations compared to conventional models. The high sensitivity demonstrates the capacity of the AI model to find the patient at risk of cardiac arrest, while the high specificity reduces many false positives and the number of interventions. The model enhanced with artificial intelligence also had a reliable area under the receiver operating characteristic (ROC) curve of 0.96[10].

B. Real time data integration

Another advantage of the AI-enhanced model included the input of dynamic physiological and more traditional patient variables. This dynamic integration allowed the model to use the latest patient data to predict instead of a set of scores. For instance, while the former methods assume the examination of data collected at the time of the patient's admission, the latter could take into account the shifts in the patient's condition, making the prognosis carried out by the AI model even more accurate and relevant.

C. Feature Selection and Importance Analysis

The results illustrated what variables could be more critical for the raised risk of cardiac arrest than others. The most prominent independent predictors of the outcome included systolic blood pressure, oxygen saturation and heart rate variability. Contrary to expectations, values such as the patient's age and medical history were less important than the physiological data usually gathered during the trial. This finding calls for current and dynamic data intervention to predict cardiac events. The proposed model also improves the interpretability of the most essential features and increases the ability of clinicians to identify critical risks in the patients.

D. Explainability of Artificial Intelligence

Although the results of the AI model were superior to the traditional methods, the problem of interpretability remained. Any variable could be explained based on feature importance and the model's SHAP (Shapley Additive Explanations) values. For instance, a reduction in systolic blood pressure and an increase in heart rate variability was associated with a raised risk of cardiac arrest across the studies, which could be helpful for clinicians.

E. Limitations of Traditional Methods

The paper also underscored the shortcomings of conventional approaches, including logistic regression and the static score, APACHE. These methods had a reasonably low sensitivity at 66% and specificity at 70%, perhaps due to the lack of flexibility in the changes in the patient's condition. Further, traditional models might have been more effective in modelling the relationships between variables as these approaches did not consider the impact of physiological data obtained in real-time from patient history. These limitations make traditional models less relevant for real-time clinical areas where the patient's status may change with high frequency and where accurate and dynamic predictive tools are required.

CONCLUSION

In conclusion, this paper using an AI-based neural network system for the prognostics of cardiac arrest revealed significant improvements in accuracy, features, and real-time data integration compared to traditional approaches. The significance of using patient demographic and physiological data variables in model development was also demonstrated, as was the application of machine learning to improve feature selection for predicting cardiac arrest events. The AI framework that captured dynamic patient data through updates has enhanced sensitivity and specificity.

Another improvement is the capability to feed the actual physiological data into the model in real-time. Limitations of conventional techniques, which depend on fixed information, include failure to capture dynamic changes of patients in critical care. When coupled with real- time data, the AI model provided a more effective way of predicting these outcomes to promote more timely actions that substantially improve patient care. The neural network also offered feature importance analysis, which was crucial when searching for predictors of cardiac arrest. In healthcare, interpretability is especially important since clinicians need to know what leads to AI's predictions to make informed decisions. Gradually, the specifics of which variables – patient age, heart rate, for instance – had the most significant effect on the changes made the model more operational and understandable to the doctors.

Compared to the models with the help of artificial intelligence, the authors revealed the deficiencies of discrete rating scales and conventional decision-making models. Whilst traditional approaches have their merits, they are not as accurate because of the inadequacy of the conventional methods in capturing the heterogeneity of patient characteristics. This paper re-emphasises the importance of artificial intelligence in decision-making, especially in areas of dire need, such as emergencies

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