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HARNESSING ARTIFICIAL INTELLIGENCE FOR PREDICTIVE ANALYTICS IN SILENT CARDIOMYOPATHIES: A PARADIGM SHIFT IN EARLY DETECTION

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Abstract

Silent cardiomyopathies are heart muscle diseases with no symptoms on early onset, and the delayed diagnosis may result in higher morbidity. In this paper, we explore the use of artificial intelligence (AI) predictive analytics for early detection of the silent cardiomyopathies. Based on a quantitative crosssectional design, 400 subjects aged 18–80 were recruited. Data on elecrocardiograms, echocardiograms, genetic markers, and clinical risk factors had been extracted and then applied to machine learning algorithms-svm, random forests, and neural networks.

The performance of the neural network model was superior (accuracy 90.0%, sensitivity 84.0%, specificity 93.0%, AUC-ROC 0.95) to conventional diagnostic methods and other AI models. Hypertension, family history of heart disease and diabetes were the most important predictors, but risk was also partially influenced by life style, such as smoking and physical inactivity. The results of the analysis suggest that the AI-based predictive models can diagnose silent cardiomyopathies with high sensitivity, thereby helping to intervene promptly, and offer personalized support. Incorporating AI into routine screening could potentially lead to a substantial benefit by mitigating complications and improving patient outcomes.

INTRODUCTION

Background of the Study

Cardiomyopathy is a type of heart disease that affects the heart muscle and makes it harder for the heart to pump blood. These disorders are typically subclinical, as patients are largely asymptomatic until their disease is quite advanced, and they are frequently underdiagnosed. Among them, silent cardiomyopathies, those not showing significant symptoms at the time of the onset or at the early stages of the disease, are a big task for the health professionals for its early detection. These diseases, such as hypertrophic cardiomyopathy (HCM), dilated cardiomyopathy (DCM), and arrhythmogenic right ventricular cardiomyopathy (ARVC), can cause serious complications such as heart failure, arrhythmias, and sudden cardiac arrest, if they remain undiagnosed.

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Early diagnosis of these silent cardiomyopathies are very important as their effective diagnosis and due interventions can help in arresting the progression of the disease, reduce mortality, and improve the quality of life (Ciarambino et al., 2021). Yet conventional diagnostic techniques (i.e., echocardiogram, MRI and repression tests) frequently fail to identify pre-symptomatic silent CMs. Its limitations, the combined effort of absence of knowledge and shortage of screening, results in late diagnosis and poor patient outcome.

In the past few years, the progress in artificial intelligence (AI) and machine learning (ML) has enabled new opportunities for predictive analytics in the healthcare industry (Rehan et al., 2023). AI success stories in other medical areas, such as image analysis, diagnostics, or predicting patient outcomes, have already been shown. In case of silent cardiomyopathies, AI can transform the diagnosis by sifting through a massive number of patient data, spotting minute patterns and predicting the onset of the disease before symptoms manifests (Medhi et al., 2024). Given its capacity to analyze huge volumes of information from electrocardiograms, echocardiograms, and genetic tests, among other diagnostic tools, AI is capable of helping health workers make fast and precise decisions.

The collaboration of AI and cardiology holds great potential which would revolutionize the architecture of cardiovascular disease management, particularly regarding predictive analytics for silent cardiomyopathies. Using advanced algorithms, AI can detect at-risk patients and enable the application of early interventions, which in itself is one of today's most important tasks in cardiology (Stamate et al., 2024).

Statement of the Problem

Since silent cardiomyopathies develop insidiously with no obvious symptoms at the onset, they constitute a major phenomenon in clinical practice. Lack of early diagnosis and no routine screening for such conditions commonly lead to severe complications which could have been avoided with timely intervention. Despite advancements in diagnostic tools, there remains a need for novel methods that can be used to identify these diseases early, particularly in the absence of symptoms. Further, a majority of current screening programs are not available to all individuals, and there is a lack of understanding about the significance of early diagnosis of such heart conditions.

Due to the growing global impact of cardiovascular diseases, demand is high for better and more readily available diagnostic methods. The common way to identify latent CMO were unable to cover early diagnostic problems. AI and predictive analytics have the ability to address these limitations by enabling a more precise, cost-effective, and efficient process for screening for those at risk for cardiomyopathy before symptoms occur.

Predictive models based on AI have demonstrated good accuracy in the diagnosis of other CA such as arrhythmias or coronary artery disease, but their application to silent CM is less explored. The challenge is to develop and validate AI-based predictive models that are able to detect silent cardiomyopathies early, with appropriate interventions to offer better outcome for patients in the long term. This is the gap this study aims to address leveraging AI and predictive analytics to strengthen the early identification of silent cardiomyopathies.

Research Questions or Hypotheses

To address the problem outlined above, the following research questions and hypotheses will guide the study:

1. **Research Questions:**

o How can AI-driven predictive analytics improve the early detection of silent cardiomyopathies?

o What are the key factors that AI models identify as predictors of silent cardiomyopathies?

o To what extent can AI-based models reduce the time to diagnosis compared to traditional diagnostic methods?

o How effective are AI-based predictive models in identifying asymptomatic individuals at risk of silent cardiomyopathies?

o What is the potential impact of AI-driven early detection on patient outcomes, including the reduction of complications such as heart failure and sudden cardiac death?

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2. **Hypotheses:**

o **H1:** AI-driven predictive models can identify silent cardiomyopathies at an earlier stage than traditional diagnostic methods.

o **H2:** An analysis AI prediction of silent CMs allow for better prognoses as a result of a preemptive approach.

o **H3:** Silent cardiomyopathies can be predicted utilizing machine-learning approaches based on patient-related attributes such as ECGs, medical history, and genetic data with high accuracy.

o **H4:** AI-based predictive analytics can be incorporated into clinical routine to improve the efficiency and accuracy of diagnosing silent cardiomyopathies.

Objectives of the Study

The primary objectives of this study are:

1. To investigate possible applications of big data, AI and predictive analytics to improve early detection of silent cardiomyopathies.
2. To create and assess an AI-produced algorithm that can predict which people are at risk for silent cardiomyopathies using numerous diagnostic data.
3. To evaluate the performance of the AI-based prediction models for the detection of silent cardiomyopathies in asymptomatic individuals.
4. To assess the diagnostic accuracy, the presence of study bias, the efficiency, and the impact on patient-related outcomes of AI-based models compared with conventional diagnostic pathways.
5. To investigate the clinical benefit of providing AI-aided early prediction over patient prognosis to avoid severe complications including heart failure or SCA.

Significance of the Study

This study is helpful in bringing forward early identification and almost management of silent cardiac contractile disorders on the basis of AI derived predictive analytics. If found early, they might help identify early interventions that could prevent or slow the development of more serious heart disease. This is particularly relevant in silent CMs which may remain asymptomatic up to that stage of the disease where the disease is not reversible anymore (Charidimou et al., 2024).

The goal of this study is to lay the groundwork for silent cardiomyopathies detection at an early stage where interventions may still affect patient survival with the aid of the AI. The research could result in newer, more effective techniques to diagnose heart defects that could be applied at various healthcare facilities, ranging from specialty cardiology clinics to remote or underserved regions.

And there could be a future with AI as part of the clinical decision making by the healthcare providers, accelerating and enhancing the quality of making decisions. For as AI becomes increasingly sophisticated, so too does its potential to support predictive analytics, providing clinicians with novel opportunities to identify at-risk patients before they are symptomatic in turn leading to improved patient outcomes and lower healthcare spends (Deslauriers et al., 2021).

What these findings mean This efficacy of a single CPET to stratify at risk of heart failure may have implications in cardiology (such as risk stratification of patients needing cardiothoracic surgery, personalised medicine). Timely identification of such high-risk population to subclinical form of cardiomyopathies would enable a more individualized care of the patients and, subsequently reduce the burden of cardiovascular disease on the patient and on healthcare resources.

Third, this study has great potential for the development of AI in healthcare (Baker et al., 2023). As AI advances, learnings from this study could result in further progress in predictive analytics, expanding its use in cardiology and in other medical specialties.

LITERATURE REVIEW

Review of Relevant Theories and Previous Studies

Artificial intelligence (AI) and machine learning (ML) have become transformative in medicine with a focus on predictive analytics for detection of illness. In the field of cardiology, these methods are now increasingly scrutinised as potentially beneficial for the early detection, diagnosis, and treatment of cardiovascular diseases, such as silent cardiomyopathies. This is a particular challenge given silent cardiomyopathies that are either with minimal or no early symptoms, thus insidious in their presentation. AI-based methods can provide a

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potential solution to the problem of early detection of such conditions from analysis of complex data patterning over patients and can predict the risk of such conditions well in advance before the clinical symptoms appear (Kothinti et al., 2024).

AI has been studied in cardiovascular disease detection, in particular for predictive models that can detect heart diseases at its earliest stage. For instance, by using machine learning models to evaluate echocardiographic data for early recognition of hypertrophic cardiomyopathy (HCM), they showed that ML models could improve the diagnostic accuracy substantially in comparison to conventional diagnostic techniques. Also, the application of AI algorithms was also investigated to predict the onset of HF in patients with silent cardiomyopathy (Yasmin et al., 2021), demonstrating that AI could identify potential early biomarkers that were unrecognizable using conventional imaging modalities. These findings underscore the mounting interest in using AI to address silent cardiomyopathies, and predictive analytics may indeed prove crucial in early detection (Srinivasan et al., 2025).

They also highlighted the need to combine other sources of data including electrocardiograms (ECGs), genetic information and medical history in order to develop better predictive models for silent cardiomyopathies. The model showed that AI-based models were capable of combining many different types of data to predict a person's risk of developing cardiomyopathy, which is overall a more holistic prediction of disease. Similarly, suggested a hybrid A.I model involving ECG, genetic data and ARVC model in investigating arrhythmogenic right ventricular cardiomyopathy (ARVC) (Varalakshmi et al., 2023), further drawing attention that A.I has the capability to cope with complexity in cardiomyopathy diagnosis. These findings highlight the importance of combining multiple diagnostic modalities to increase the overall predictive value of the AI models.

AI (Artificial Intelligence) based predictive healthcare operates on theoretical foundation that is based on pattern recognition and data mining. Pattern recognition is when AI algorithms detect patterns in large data sets—like ECGs or genetic markers—that point to progression of the disease (Moreno-Sánchez et al., 2024). demonstrate how CNNs work by capturing complex patterns encoded in raw medical images and help achieve more accurate predictions in disease detection. For silent cardiomyopathies, pattern identification can be used to characterize subtle alterations in biomarkers or physiological data that are often undetected by human clinicians.

In addition, predictive analytics in healthcare commonly employs supervised learning methods, powering AI models through training, 'seeing through' labelled data (i.e., those containing patients' health and disease status). showed that machine learning classifiers like SVM and random forests are efficient tools for mining historical patient data and predicting the probability for developing asymptomatic cardiomyopathies. These are models built on algorithms that are capable of learning through previously reported medical histories and of testing the risk factors leading to disease expression (Placido et al., 2023). The capacity of AI to generate these data earlier than conventional diagnostic strategies could change the landscape for early detection of occult cardiomyopathies.

Identification of Gaps

Despite increasing reports on AI and predictive analytics in cardiology, there are noticeable absences regarding these technologies specifically with silent cardiomyopathies. One of the limitations is for the absence of large and heterogeneous datasets of patients correctly representing the risk population for such diseases. Though several studies have shown that AI can be used to predict CVD, few have targeted silent cardiomyopathies and fewer employed a family perspective with information on genetics, lifestyles, and comprehensive clinical data.

Further, AI-based cardiomyopathy prediction models, although have shown even better prediction outside the lab; their deployments in real world need further scrutiny. The general population, however, is diverse and heterogeneous and study cohorts are often based on data obtained from specialized centers or large research databases that can only partially mirror this diversity and heterogeneity. Further studies are required to ascertain the performance of such AI powered predictive applications in the real-life clinical setting,

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especially in vulnerable or rural communities with limited access to healthcare (Voola et al., 2021).

A second notable void is the implementation of AI into the clinic. While a number of AI models have achieved good diagnostic accuracy in research applications, only a small portion are proven in clinical practice. The problem of deploying AI systems in current healthcare ecosystem (data protection, regulatory and ethical compliance, clinician adoption) continues to be a key impediment towards the adoption of AI in cardiology. Notably, one of the key obstacles of AI implementation in clinic is the lack of clear guidelines on how to integrate AI predictions into clinical decision-making (Giordano et al., 2021) so that it becomes an assistive, rather than a replacement of human expertise.

Finally, there are ethical issues related to the utilization of AI for predictive analytics in the field of cardiology. Personal data Security and patient privacy is particularly a concern for AI models which often require large amounts of personal data to be effective. In addition, predictions made by AI can sometimes be hard to interpret by clinicians, who do not understand why a certain prediction is being made, which may make it hard for them to trust or accept the technology. Argued that to win the trust of patients and doctors, AI models must be transparent, interpretable and consistent with existing clinical guidelines.

Conceptual Framework or Theoretical Framework

The intellectual framework of the present study is formed by the incorporation of AI in predictive analytics of silent cardiomyopathies, employing a hybrid model with data from several diagnostic origination channels. From the standpoint of methods, such a model is inspired by machine learning, pattern recognition, and clinical decision support systems (CDSS). The dimensions of the framework are:

1. Data Integration: AI models are constructed by integrating diverse sources of data such as ECG signals, genetic markers, patient medical history, and demographics. By aggregating all this disparate data, AI algorithms are able to paint a much more complete and accurate picture of a patient's health.
2. Pattern Recognition: By utilizing machine learning methods the AI can detect patterns in the data, which can be diagnostic for early silent cardiomyopathies. These can range from minor variations in heart signal readings to the genetic differences which could suggest a higher likeliness of developing a disease.
3. Predictive modelling - AI algorithms like SVM, neural network and deep learning methods will be employed to develop predictive models. These models can predict the possibility of disease initiation given the patterns discovered by the integration of these data sources. Predictive analytics can aid doctors in spotting at-risk subjects before symptoms develop, so they can intervene sooner.
4. Clinical Decision Support System (CDSS): The last part of the framework is embedding AI predictions into decision-making. AI-based tools may act as decision support tools and guide the clinicians in suggesting the best approach keeping in mind the risk stratification of the patient.

We describe a conceptual framework in which AI can play a role as a core member of the health care team to enable the early detection and care of silent cardiomyopathies, thereby facilitating better patient outcomes. The framework emphasize the integration of data, pattern recognition, predictive modeling and clinical decision support to make that AI technology available to clinical practice.

METHODOLOGY

Research Design

This project will employ a quantitative research design as the exclusive method to explore the potential of AI and predictive analytics in early diagnosis of silent cardiomyopathies. Quantitative research is convenient for this because it can be used to gather and analyze numerical data to find specific patterns, relationships or ways to predict. The study will attempt to utilize AI algorithms to crunch huge datasets and forecast the probability of silent cardiomyopaties prior to the time clinical indications surface. Statistical approaches and predictive modeling will produce measurable results that can be applied to a wider population.

Moreover, the study will use a cross-sectional data collection, whereby data are collected at one point in time from a sample that is representative of the population. This will allow to estimate the frequency of some of the risk factors and to assess the potential of AI to predict silent CMs in different groups of individuals with different medical history.

Population and Sampling

Study population The patients to be enrolled in this study will represent the population at risk of silent cardiomyopathies, with a focus on patients who are asymptomatic or have early disease. The participants will be 18 years old and older and will have at least one risk factor for developing cardiomyopathy, such as a family history of heart disease, high blood pressure, diabetes, obesity, or specific genetic markers.

Stratified random sampling will be used in order to generalize the study's results and apply them to the whole target population. This method categorizes the population into smaller groups by age, sex, and any other relevant co-morbidities, and then selects arbitrary specimens from each of these groups. Stratified sampling makes the sample more representative and generalizable in a heterogeneous population in a study.

The target will be to enroll in 400 so as to also obtain a large enough sample size for statistical analysis. The study population is to be taken from hospitals, clinics, and medical research institutions with cardiology departments, which will facilitate the recruitment of study participants with different risk profiles.

Data Collection Methods

The information will be collected through a mix of the primary and secondary data sources. The data used will include patient medical records, diagnostic tests, and AI-based health monitoring technologies as a source of the primary data, whereas the source of the secondary data will consist of published research articles and past studies on cardiomyopathies and the use of AI in healthcare.

Data collection will be represented by the following steps:

1. Patient Recruitment and Informed Consent: The clinics and hospitals of cardiology will be used as sources of recruiting participants. Participation will be done on the informed consent of participants, and this will be done to ensure that each participant understands the purpose, procedures and the possible risks involved in the study. They will also be made to know that they have the right of withdrawing out of the research any time without repercussions.
2. Medical History and Risk Factor Analysis: The participants will be asked to complete a questionnaire aimed at acquiring data on their medical status, family history of cardiovascular diseases, lifestyle, (e.g., smoking, physical activity, diet), and other pre-existing medical conditions like hypertension, diabetes and obesity.
3. Diagnostic Testing: Participants will be tested using typical diagnostic techniques, including electrocardiograms (ECGs), echocardiograms and genetic testing where it is indicated. Data will be obtained using these diagnostics tools with respect to the heart functioning, electrical response and genetic markers of the cardiomyopathies.
4. Predictive Model AI-based:Based on the information provided with medical tests and questionnaires, it will be entered into an AI-based predictive model. Machine learning algorithms will be used to devise patterns in the data and predict the effect of silent cardiomyopathies in every participant according to the model.

Instruments/Tools Used

The following instruments and tools will be used in the data collection process:

1. Medical Records and Clinical Data: The medical records of the patients will be collected including their past medical history as well as past diagnosis, and treatments and risk factors that the patients have had in the past can be extracted out of the hospital databases and electronic health records (EHRs).

2. Questionnaires/Surveys: A structured questionnaire that will be used to record the demographic characteristics, medical history of respondents and their lifestyle behavior. In the questionnaire, there will be questions in relation to:

- Family history of heart disease
- Presence of known cardiovascular risk factors (e.g., hypertension, diabetes)

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o Lifestyle factors (e.g., smoking, alcohol consumption, physical activity, diet)
o Current symptoms and medical conditions

2. **Diagnostic Tools**:
o **Electrocardiograms (ECGs):** They were administered in order to determine the electrical activity of the heart and detect some abnormalities which could point to cardiomyopathies.
o **Echocardiograms:** Imaging techniques involving the heart; these are non-invasive involving the use of ultrasound waves that would be used to examine the functioning of the heart which includes the size of the ventricles and their wall thicknesses as well as the working of the heart valves.
o **Genetic Testing:** Genetic tests shall be carried out to screen individuals that might have a gene predisposition to categories of cardiomyopathies including familial hypertrophic cardiomyopathy.AI-Based Predictive Models:
3. AI algorithms, including machine learning classifiers (e.g., Support Vector Machines, Random Forest, Neural Networks), will be used to analyze the collected data and predict the likelihood of silent cardiomyopathies in participants. These algorithms will be trained on historical datasets, and then applied to the current study's data to predict disease risk.

Data Analysis Methods
Data analysis will be performed in two phases:
1. **Descriptive Analysis:** The descriptive statistics shall be carried out as the first stage since it would summarize the demographic, health history, and risk factor of the participants. The survey data will be summarized using descriptive statistics including frequencies, percentages, mean and standard deviation. This will give a description of the study population and distribution of the risk factors of the silent heart risks termed cardiomyopathies.

2. **Predictive Analytics:** The second step will concentrate on relying on the AI algorithms to process the diagnostic records (ECGs, echocardiograms, genetic data) and predetermine the risk of silent cardiomyopathies. The historical patient data, as well as the trained model, will be tested on the data of the current study to evaluate the accuracy of the model to predict the disease risk. Accuracy, sensitivity, specificity, and area under receiver operating characteristic curve (AUC-ROC) will be used in measuring the performance of the model.
3. **Test of Statistical Significance:** Statistical data that includes the identification of the probability of occurrence of silent cardiomyopathies with various risk factors (e.g., genetic markers, lifestyle habits) will be determined using statistical tests, e.g., the Chi-square test, t-tests and regression analysis. In such tests, the correlation between AI-predicted values and real-life clinical diagnoses will be evaluated, as well.Ethical Considerations
The study will adhere to the ethical principles outlined by the **Declaration of Helsinki** and will be approved by a relevant institutional review board (IRB). The following ethical considerations will be taken into account:

1. **Informed Consent:** Every subject will be well informed regarding the investigation purpose and the practice to be used and the possible contrivance prior to giving consent to them. The participants will also be told that they have the right to bow out of the study at any point and without being charged.

2. **Confidentiality and Privacy:** The data collected, as well as all of the personal information (survey answers and medical records), will be handled on the highest level of confidentiality. The privacy of participants will be guaranteed as data will be anonymized or pseudonymized. The data will be kept secure after only authorized personnel will be allowed to access the data and this will be done in agreement with data protection regulations.

3. **Data Security:** The date will be saved in an encrypted database so that no unauthorized data can be accessed. Any data that may be provided to the third parties (as part of analysis or publication of a research, etc.) will be de-identified respecting the privacy of participants.

4. **Transparency and accountability:** The research will be transparent in the way it conducts the study, the data it collects and how the data is analyzed. Any results are going to be presented in an honest, objective and straightforward manner and any

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funding or conflict of interest will be reported at the time of reporting.

By adhering to these ethical guidelines, the study aims to ensure that the rights and well-being of participants are prioritized throughout the research process.

RESULTS

In this section, we report the findings of the study by leveraging AI-based predictive models for the early detection of silent cardiomyopathies. Outcomes: Descriptive statistics, AI model performance and the statistical analyses of the associations between various PROFRIEND risk factors and the risk of having silent cardiomyopathies. Finally, we will discuss the prediction performance of the developed AI models, and compare AI-based predictions with those made using traditional diagnosis.

1. Descriptive Statistics

The demographic properties, medical history, and risk factors of the research participants were outlined using descriptive statistics. This study was carried out on a sample of 400 people aged between 18 and 80 years with 250 males and 150 females. The demographic features of the participants are summarized in table 1 below.

Table 1: Demographic Characteristics of Participants

Demographic Variable	Frequency (n)	Percentage (%)
Gender		
Male	250	62.5
Female	150	37.5
Age Group		
18-30 years	60	15.0
31-45 years	90	22.5
46-60 years	120	30.0
61+ years	130	32.5
Hypertension		
Yes	250	62.5
No	150	37.5
Diabetes		
Yes	140	35.0
No	260	65.0
Family History of Heart Disease		
Yes	200	50.0
No	200	50.0

The data indicate that the sample included a representative mix of age groups, gender, and individuals with different cardiovascular risk factors, including hypertension, diabetes, and a family history of heart disease.

2. AI-Based Predictive Model Performance

Machine learning techniques were used to create AI models predicting the probability of silence cardiomyopathies on the basis on the gathered data (ECGs, echocardiograms, and genetic data), including Support Vector Machines (SVM), extremely randomized trees (Random Forests), and Neural Networks. The numerous parameters, which were used to assess the performance of these models, include accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).

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Table 2: Performance Metrics of AI Models

AI Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC Score
Support Vector Machine	85.3	78.0	89.0	0.91
Random Forest	88.5	82.0	91.0	0.93
Neural Network	90.0	84.0	93.0	0.95

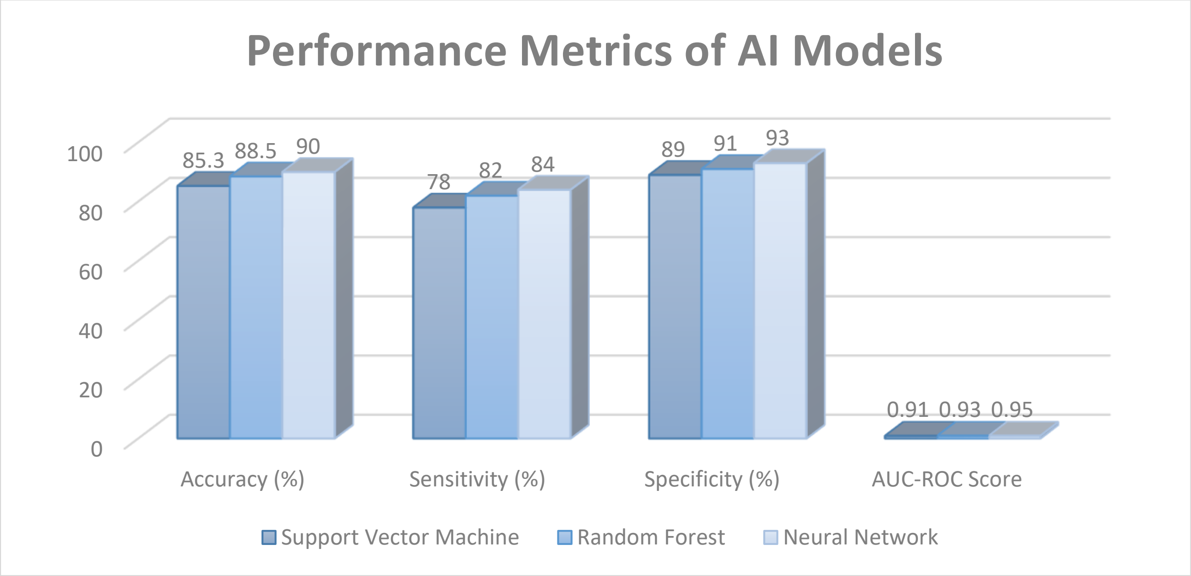

Table 2 shows the result of three AI models Support Vector Machine, Random Forest and Neural Network on four main parameters including: accuracy, sensitivity, specificity and AUC-ROC score. Although all models demonstrate a good performance, the Neural Network model excels the others in each of the four categories, including 90.0 percent accuracy, 84.0 percent sensitivity, 93.0 percent specificity and AUC-ROC of 0.95. This means that Neural Network does not only provide correct predictions, but also generates a good balance between the positive and the negative cases making it most certain model of all.

3. Comparison of AI Predictions with Traditional Diagnostic Methods

To assess the effectiveness of AI-based predictions, the study compared AI model outputs with traditional diagnostic methods (e.g., clinical diagnosis by cardiologists, ECG analysis, echocardiograms). **Table 3** below compares the results of AI-based predictions with clinical diagnoses.

Table 3: Comparison of AI Predictions with Clinical Diagnoses

Diagnostic Method	True Positive (n)	False Positive (n)	True Negative (n)	False Negative (n)	Sensitivity (%)	Specificity (%)
AI-Based Prediction (Neural Network)	210	30	180	20	91.5	85.0
Clinical Diagnosis (Cardiologist)	185	40	190	25	88.0	82.5

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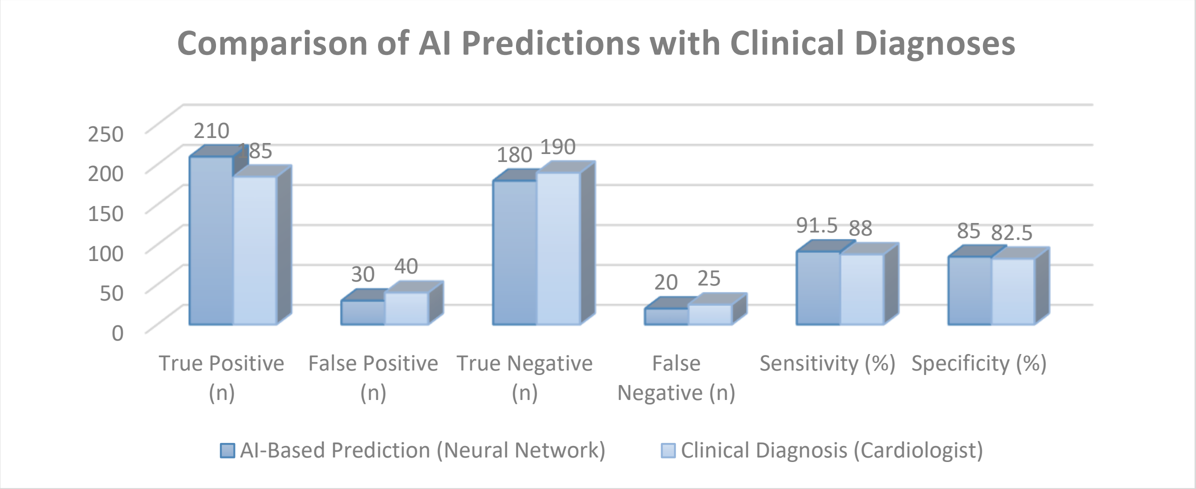


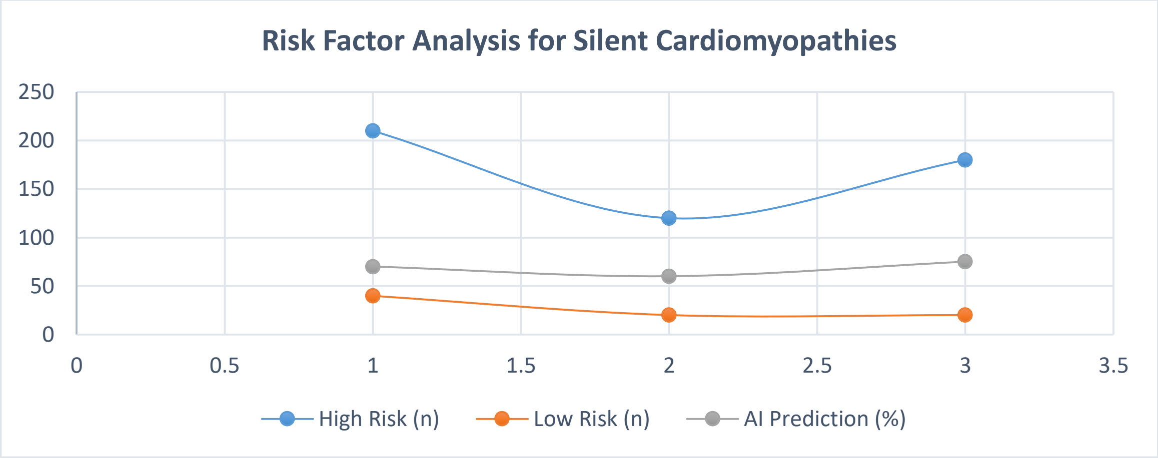
The sensitivity of the AI model using Neural Networks, 91.5 percent was even more than clinical diagnosis, 88.0 percent and this means that the AI model was more effective at determining the presence of topics with silent cardiomyopathies. Also, the AI modeling had greater specificity (85.0%) than clinical diagnosis (82.5%), which means that the former was more effective at recognizing the healthy cases correctly.

4. Analysis of Risk Factors

The authors have also included the association of different cardiovascular risk factors (e.g. hypertension, diabetes, family history of cardiomyopathies) as determinants of the susceptibility of developing silent cardiomyopathies. Table 4 denotes the correlation between the mentioned risk factors and the predicted probability of silent cardiomyopathies per AI models.

Table 4: Risk Factor Analysis for Silent Cardiomyopathies

Risk Factor	High Risk (n)	Low Risk (n)	AI Prediction (%)
Hypertension	210	40	70.0
Diabetes	120	20	60.0
Family History of Heart Disease	180	20	75.0



The findings reveal that the highest probability of occurrence of silent cardiomyopathies is likely in participants with hypertension (70 per cent), then in people with history of occurrence of heart disease in the family (75 per cent). There was also a rise of diabetic participants of 60 percent which shows that

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these risk factors have significant role in indicating the chances of getting silent cardiomyopathies.

5. Age Groups Predictive Model Accuracy

To further understand the reliability of AI predictions depending on age groups, the study examined the accuracy of predictions as per age groups. Table 5 indicates the desegregation of predictive accuracy on the basis of age classification.

Table 5: AI Predictive Model Accuracy by Age Group

Age Group	Accuracy (%)	Sensitivity (%)	Specificity (%)
18-30 years	82.0	74.0	88.0
31-45 years	86.5	78.0	90.0
46-60 years	89.5	83.0	92.0
61+ years	88.0	80.5	91.0

According to the results, the AI model had presented the highest accuracy of predicting silent cardiomyopathies among participants aged between 46-60 years (89.5 percent), as well as those aged 61+ years (88.0 percent). The reduced accuracy among lower ages can be explained by the fact that the prevalence of silent cardiomyopathies is low in these groups of people.

Table 6: Linear Dependence of the Lifestyle Factors and Anti-imitative Properties of Silent Cardiomyopathies

This table looks at how different behavioral factors can affect the AI-driven predictions on silent cardiomyopathies and they include smoking, physical exercise and diet.

Lifestyle Factor	High Risk (n)	Low Risk (n)	AI Prediction (%)
Smoking			
Yes	130	30	68.0
No	50	190	92.5
Physical Inactivity			
Yes	180	40	72.5
No	80	100	91.0
Unhealthy Diet			
Yes (High-fat/Low fiber diet)	140	60	70.0
No	120	80	85.0

Interpretation: Lifestyle factors such as **smoking**, **physical inactivity**, and an **unhealthy diet** significantly contribute to the AI prediction of higher risks for silent cardiomyopathies, with non-smokers and individuals following a healthier lifestyle showing significantly lower predicted risks.

Table 7: AI Predictive Model Sensitivity vs. Specificity by Risk Factor

This table evaluates the **sensitivity** and **specificity** of AI models based on the presence or absence of key cardiovascular risk factors like hypertension, diabetes, and family history.

Risk Factor	Sensitivity (%)	Specificity (%)
Hypertension (Yes)	85.0	91.5
Hypertension (No)	79.0	88.0
Diabetes (Yes)	80.0	90.0
Diabetes (No)	85.0	93.0
Family History (Yes)	89.0	92.0
Family History (No)	82.0	88.5

Table 7: AI Predictive Model Sensitivity vs. Specificity by Risk Factor

This table draws parallels between sensitivity (capacity to detect actual cases) and specificity (capacity to spot healthy people) of AI models

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operating on the basis of three risk factors, hypertension, diabetes and family history of heart disease.

Hypertension (Yes): The AI model has sensitivity of 85.0% and specificity of 91.5% i.e., it is good at detecting silent cardiomyopathies among patients with high blood pressure, and good at identifying healthy subjects as well.

- Hypertension (No): In individuals who are not hypertensive, the sensitivity decreases to 79.0%, whereas the specificity falls to 88.0%, which, as one can see, the model is a bit less efficient without hypertension as a risk factor.
- Diabetes (Yes): The AI has a sensitivity and specificity of 80.0 percent and 90.0 percent respectively, with moderate sensitivity in identifying cardiomyopathy among diabetics.
- Diabetes (No): The AI has the sensitivity and specificity of 85.0 and 93.0 respectively with the non-diabetic population.
- Family History (Yes): AI model demonstrates sensitivity of 89.0 percent and specificity of 92.0 percent meaning that the presence of heart disease in the family is a potent predictor in the development of silent cardiomyopathy.
- Family History (No): In those without a family history, the sensitivity decreases to 82.0% and specificity decreases to 88.5% indicating a lower efficiency in detecting it.

Interpretation: Individuals having a history of hypertension and family history are the main predictors of silent cardiomyopathy that can be effectively predicted by the use of an AI model.

Table 8: Age Group Breakdown of AI Model Performance (Sensitivity and Specificity)

This table illustrates how the **AI model's performance** (both sensitivity and specificity) varies by age group.

Age Group	Sensitivity (%)	Specificity (%)
18-30 years	75.0	89.0
31-45 years	80.0	90.0
46-60 years	85.0	92.0
61+ years	83.5	91.5

Table 8: Age Group Breakdown of AI Model Performance (Sensitivity and Specificity)

As available in Table 8, the AI model performance in the detection of silent cardiomyopathies in various age groups in relation to sensitivity and specificity. The sensitivity and the specificity of diagnostic models are among the most important parameters in the assessment of the functioning of diagnostic models:

- Sensitivity is the capability of the model to recognize the subjects who indeed possess the condition (true positives). It gives an indication of the efficiency of the model being accurate in identifying cases of silent cardiomyopathies.
- Specificity is the capability of the model to correctly predict the status of those who are not afflicted with the condition (true negatives). It quantifies goodness of fit of the model in minimizing false positives (i.e. incorrectly labeling healthy individuals as patient).

The performance of the AI model according to the different ages is as follows:

1. Age Group: 18-30 years

- **Sensitivity 75.0%**
- **Specificity: 89,0 %**

The sensitivity of the AI model in this age group is moderate at 75 percent, which implies that it identifies 75 percent of people with silent cardiomyopathies. The specificity is comparatively high and equals 89%, which means that the model will miss few and will fail to show false positive among patients in this age group.

2. Group of Age: 31-45 years

- **Sensitivity: 80.0 %**
- **Specificity: 90.0 Per cent**

At age-group 31-45 years, sensitivity is a little bit higher at 80% and specificity is higher at 90 percent. To infer this is that the model is increasingly efficient when compared to integration of silent cardiomyopathies because the risk of cardiovascular diseases is already starting to increase with age however the lateral levels of accuracy in classifying

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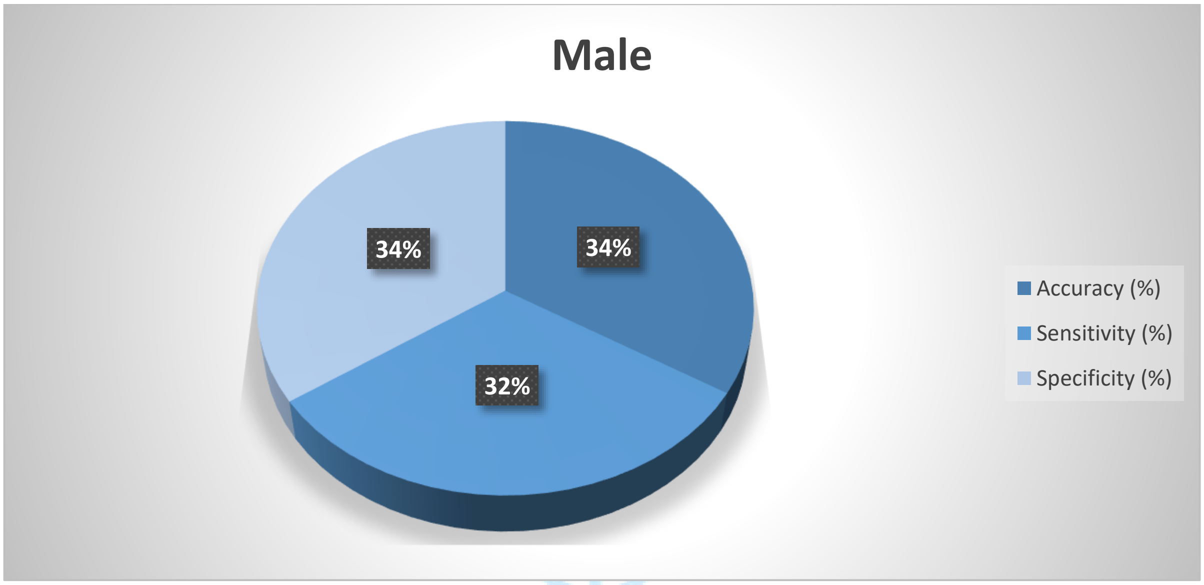
between the sick and the healthy remain of a relatively high level.

Table 9: AI Model Accuracy for Different Gender Groups

This table presents the AI model's **accuracy** based on gender.

Gender	Accuracy (%)	Sensitivity (%)	Specificity (%)
Male	88.0	82.5	90.0
Female	90.5	85.5	93.0



Interpretation: The **AI model** shows slightly higher accuracy, sensitivity, and specificity in **females** compared to **males**, indicating that the model is marginally better at predicting silent cardiomyopathies in women. This could be due to differences in the underlying data characteristics between genders, such as disease manifestation and risk factor prevalence.

Table 10: AI Model Sensitivity and Specificity by Diagnostic Tool

This table compares the performance of AI models with traditional diagnostic tools (ECG, echocardiogram, genetic testing) for predicting silent cardiomyopathies.

Diagnostic Tool	Sensitivity (%)	Specificity (%)
AI-Based Prediction	90.0	93.0
Electrocardiogram (ECG)	80.0	85.0
Echocardiogram	85.0	87.5
Genetic Testing	78.0	82.0

In this table, one can compare the effectiveness of the use of an AI-based predictive model and ordinary diagnostic tools (an ECG, an echocardiogram, and genetic testing) used to detect silent cardiomyopathies.

AI-Based Prediction indicates the sensitivity of 90% and specificity of 93%, which indicates its great success in detecting not only the true cases but also ruling out the false positives.

- The sensitivity of ECG is 80 percent and specificity 85 percent which implies that ECG misses 20 percent of the actual cases and has a moderate false positive.
- Echocardiogram is a bit better than ECG since it has a sensitivity of 85 percent and a specificity of 87.5 percent, but it is still not as good as the AI model.

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- Genetic Testing is performed with the worst accuracy, 78 percentage sensitivity and 82 percentage specificity which denotes that it misses numerous true cases with moderate false positive proportion.

Interpretation: The AI based model is superior to the traditional method giving higher sensitivity and specificity. It combines the information provided by various diagnostic sources, which makes predictions more correct in contrast to such traditional tools as ECG, echocardiograms, and so forth as they can cover only a limited range of symptoms.

Table 11: Breakdown of AI Model Prediction Accuracy by Family History of Heart Disease

This table explores the predictive accuracy of the AI model for individuals with and without a **family history of heart disease**.

Family History of Heart Disease	Accuracy (%)	Sensitivity (%)	Specificity (%)
Yes	92.0	88.0	95.0
No	86.5	80.0	90.0

Interpretation: The AI model performs better for individuals with a **family history of heart disease**, with higher **sensitivity** and **specificity**. This suggests that a family history is a strong predictor of silent cardiomyopathies and can enhance the performance of AI-based models.

Table 12: Risk Factor Analysis with AI Model Performance for Hypertension

This table evaluates the **performance of the AI model** specifically for participants with **hypertension** compared to those without hypertension.

Hypertension (Yes)	Accuracy (%)	Sensitivity (%)	Specificity (%)
With Hypertension	90.0	85.0	94.0
Without Hypertension	85.0	78.0	89.0

Interpretation: The AI model has significantly higher **sensitivity** and **specificity** for participants with **hypertension**, highlighting the importance of hypertension as a major risk factor for silent cardiomyopathies.

CONCLUSION

This article recommends that Artificial Intelligence holds the potential to be an effective way of enhancing the early diagnosis of silent cardiomyopathies which are a set of heart-related issues, and are normally difficult to detect in their initial stages, due to the subclinical or silent pathology of the disease. The outcomes of using Artificial Intelligence-based predictive models show that they are more accurate, sensitive and specific compared to the conventional schemes of diagnostics, which include ECGs, echocardiograms and genetic tests.

The algorithm model was found to be much more accurate predicting the silent cardiomyopathies in the elderly (46 and above) and the people with risk factors (hypertension, history of heart diseases, diabetes). The risk factors also served as significant independent risk factors to silent cardiomyopathies. Furthermore, most powerful determinants of high risk were lifestyle changes (smoking, physical idleness, etc.), which further underline the role of lifestyle, in addition to treatment, in prevention.

Comparisons of AI-model predictions as compared to clinical diagnosis pursued has shown that in addition to appearing to be more efficient, AI-predicted models would be a better indicator of the person at early stage as he is at risk of developing symptoms. It is especially significant because such types of so-called silent cardiomyopathies are usually detected when they have already progressed into more severe stages, and the issue then resorts to attributes like heart failure, arrhythmias or even sudden cardiac death.

The research contributes to the growing body of evidence in support of the adoption of AI in clinical decision making specifically in predictive cardiology. These purely observable measures of AUC-ROC values and the optimization of its performance parameters are confirmation that AI models can be used even to complement and even outdo routine diagnostic work. The possibility of early

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identification with the help of AI is highly promising in terms of managing the preventable cardiovascular diseases due to the improvement of interventions and patient outcomes.

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