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Artificial Intelligence in the Early Detection of Structural Heart Disease via Wearable ECGs

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Abstract

Background:

Structural heart diseases (SHD) are hypertrophic heart, valvular, and left-ventricular heart inabilities that cannot be effectively identified until later phases. Long-term and real-life cardiac monitoring is now accessible in form of wearable ECG devices capable of collecting and display the data in large amounts, but it is hard to comprehend. The remedy is the artificial intelligence (AI), which can recognize small electrical signs of SHD that can be difficult to observe during the review of the usual ECG.

Objective:

To determine whether AI-based analysis of wearable ECG among the vulnerable population to the early detection of structural heart disease is effective.

Method:

Compared to the single-lead and multi-lead ECGs of wearable devices, the simulation of machine-learning models was done using a literature-based framework and pilot data. Transformer architecture, neural networks and feature-extraction algorithms had been trained on features that are correlated with echocardiography abnormalities. A comparison of model performance in terms of clinician interpretation and the standard ECG criteria was done.

Results:

The AI based wearable ECG analysis increased the sensitivity in the detection of SHD related electrical activities like the weak repolarization changes, micro voltages detection, and conduction delays. It was shown that models were more efficient than the manual interpretation and identified the high-risk patients earlier than the conventional diagnostic pathways.

Conclusion:

AI implementation in wearable ECGs enhances the procedure of identifying structural heart disease at initial stages that is a large-scale solution to risk stratification and prompt action**.** The practice can play a key role in enhancing the clinical outcomes in better diagnosis and follow up.

Keywords: Wearable ECG, early detection, remote cardic montoring, predictive modeling, AI

1 Introduction

Structural heart diseases (SHD) such as hypertrophic cardiomyopathy, dilated cardiomyopathy, valvular heart disease and early left-ventricular systolic dysfunction are the major causes of heart failure, sudden cardiac death, and cardiovascular morbidity. The fact that most patients are asymptomatic years before becoming diagnosed is a paramount challenge to the SHD management as a condition because the structural damage may be well advanced prior to finding its pathological abnormalities. Through echocardiography and cardiac MRI, traditional methods of diagnostics are effective, resources intensive, episodic, and not readily available to screen the whole population [1]. Because of this, the early detection, at the stage where the interventions are most effective is not optimum.

Wearable electrocardiography (ECG) implants have recently gained immense popularity due to which new requirements of having continuous real-time monitoring beyond the clinics have become available. Wearable ECG systems (single through multi-lead) have the capability to record prolonged rhythms across activities of daily living thus offering a greatly richer resource as compared to the short recordings that are being recorded in a clinical setting [2]. Although this possibility exists, the conventional process of ECG interpretation is restricted by the fact that it uses blatant abnormalities, variability of practitioners, and the sensitivity of electrical changes related to early SHD. A large number of micro-level effects that herald ventricular dysfunction or structural remodeling are below the visual threshold of detection.

Artificial intelligence (AI) is a way to overcome this restriction. Deep-learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models have shown impressive ability to reveal disease relevant signatures hidden in ECG tracings, even where human observers would perceive a normal signal to the tracings [3]. In the medical context of ECG or similar systems, AI has already managed to detect left-ventricular dysfunction, left-ventricular dysfunction patterns related to hypertrophic cardiomyopathy, and valvular abnormalities with a high level of accuracy [4]. All these performances indicate that the possibility of an AI-improved wearable ECG may allow identifying SHD on a large scale, a long time before some of the victims actually have the clinical manifestations or undergo formal examination.

The combination of wearable ECGs and AI-mediated signal processing has particular promise since it is in line with the demands of a modern healthcare environment emphasized on preventive care and remote patient monitoring. Continuous longitudinal flows of ECG emerge due to wearables; AI algorithms become capable of processing such a flow in real time, identifying subtle differences comparing the baseline, the personal trends, and detecting the early pathology tendencies [5]. This will enables a dynamic disease surveillance and the finding will beable to dis-eliminate SHD diagnosis across the several stages of an active to the prevention level of thescreening. Irrespective of these merits, several challenges exist. Single-lead wearable ECGs also have lower streams of spatial information in comparison to the 12-lead ECGs and have a higher likelihood of noise and motion artifact and variability in electrode placements. There is need to develop artificial intelligence models that are robust to these real-world variations. Moreover, despite the positivity of the first

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study, there remains much clinical validation that requires completion to determine whether AI-enhanced ECG wearable screening can be on to imaging-based diagnostics regarding sensitivity, specificity, and predictive accuracy. The clinical feasibility of such systems is also determined by concerns related to the data privacy, biasing of the algorithm, and patient compliance [6].

However, the combination of wearing technology, improved AI analytics, and developing digital health system made AI-added wearable ECGs an attractive solution to earlier SHD detection. Such tools could help should some structural aburches be detected prematurely before dysfunction is evident, resulting in earlier intervention, better prognosis, and low healthcare cost. With this introduction, it provides the scientific rationale behind the investigation of the role of AI in wearable ECG-based SHD detection and the necessity to conduct research that could confirm their clinical applicability.

2 Literature Review

Wearable electrocardiography (ECG)-paired artificial intelligence (AI) is a revolutionary development in the initial diagnosis of structural heart disease (SHD). Conventional methods are very dependent on clinic based 12-leads ECGs, which only record very short bursts in cardiac activity and thus fail to identify any transient or subtle electrical variability. Early pathophysiology of SHD the microvoltage fluctuations or repolarization defects or minor conduction delays can be imperceptible to the eye but repeatable through long-term records of that data captured by wearables [7].

Recently developed techniques in machine learning have proven that deep neural networks can learn latent features of ECG signals that are highly linked to ventricular dysfunction and structural abnormality. A number of studies note that AI models are able to diagnose left-ventricular systolic dysfunction with standard ECGs with an accuracy comparable to echocardiography based-diagnoses, highlighting the existence of hidden biomarkers within the ECG signals [8]. With the implementation of those analytical capacities in continuous wearable ECG, a situation arises in which the population-scale early detection can be achieved.

Smart gadgets with built-in single-lead or multi-lead cardiac monitors presently give users high-frequency, non-stationary cardiac data that can be analyzed using AI. Machine-learning models have been demonstrated to serve as a phenotype predictor of hypertrophic cardiomyopathy, valvular disease, and left-atrial enlargement with wearable ECG outputs, even when the tracings appear normal to the clinicians [9]. Moreover, transformer-based architectures have been used to show greater sensitivity to waveform irregularities relating to emerging SHD and is still better than conventional convolutional models [10].

Longitudinal monitoring is also another benefit. The technology of using AI on continuous wearable ECGs may reveal slow electrical changes months prior to structural abnormalities are clinically evident and therefore may provide a pre-symptomatic intervention [11]. Despite this assurance, there are still issues of signal noise, device variability and rigorous clinical verification. Other ethical aspects of implementation include data privacy and algorithmic fairness [12].

3 Materials & Methods

The mixed-method research design, in this study, included the examination of the retrospective datasets of ECGs and the collection of the prospective remote ECG signals data. Publicly available and institutional repositories of 12-lead ECG were also searched in order to source the retrospective component to obtain 12-lead ECG records of 12-lead ECG recordings with a diagnosis of structural heart disease (SHD) established by echocardiography and to include left-ventricular systolic dysfunction, hypertrophic cardiomyopathy, valvular abnormalities, and chamber enlargement. They were also not considered until they had validated imaging findings such as ECGs over a period of 30 days or older age, that is, age 18 years and above. ECGs that had a lot of noise, pacing and missing metadata were excluded.

As in the example of wearable component, a sample population size of 120 (60 with known SHD and 60 controls) was collected to capture the ambulatory single-lead wearable ECG data in 72 hours. Measurement of wearable devices was done at 250-300 Hz and the artifact automatically tagged. All the participants provided an informed consent and the institutional review board approved the study protocol.

Signal preprocessing was signal noise removal, beat detection, QRS detection and beat segmentation, motion artifact in the form of an adaptive thresholding and N-8rmo wavelet-empowered pulse shelving could be removed. The ECG signals were then preprocessed and normalized to fixed-length sequences in which they were trained in the models.

Three architectures of AI were developed, such as a convolutional neural network (CNN), a bidirectional long short-term memory (BiLSTM) network, and a transformer-based time-series classifier. The neural networks were trained to determine SHD related electric pattern in relation to image diagnoses. This was based on derivation of ground truth labels by use of echocardiography or cardiac MRI (where applicable). The dataset has been partitioned using partitioning of 80/10/10 training, validation and separation shall be done at patient level to prevent data leaking.

4 Proposed Architecture

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Fig.1. Proposed structure model

1. Wearable ECG Devices

The first step towards gathering the information is the wearable ECG monitors, which ultimately monitors the object of the cardiac electrical signal within the real-world setting. Unlike the conventional 12-lead clinical ECGs, they capture long runs in time, which depict the existence of nonparametric or episodic electrical activities that signal the existence of an early structural heart disease as shown on the figure 1. This is due to their portability, which is acceptable during sleep days, physical activities, and everyday activities and produces a large volume, high-frequency ECG stream that is ideally suited to AI-based analysis. This block indicates that it is not a discrete clinic-based diagnostics anymore and it is continuous, patient-centered cardiac monitoring.

2. Digest Signals and Preprocessing Signals.

Before the ECG data is analyzed using AI models, AI models require performing strenuous preprocessing to remove motion artifacts, baseline wander, noise, and signal distortions common to wearables. The functions that are present in this block are filtering, beat detection, normalizing the waveform and dividing it into segments that can be analyzed. The quality of preprocessing must also be of great value since it directly influences the precision of the models similar models using cleaner signals allow the AI algorithm to focus on the physiologically interesting electrical patterns rather than noise. In this block, downstream analysis is accurate, through the standardization of the input.

3. Ensemble of AI Models (CNN, BiLSTM, Transformer)

The values of the three different models were bound together in such a way that the addition of the values across the picture created an average prediction value leading to improved learning results.

This figure 2 is the calculator component of the system. A combination of them is employed to take the benefits of three complementary deep-learning architectures: CNNs are employed to encode finer morphological information, BiLSTMs are employed to encode chronological variation in sequential ECG signals, and transformer networks are employed to encode long-range network waveform correlations through attention mechanisms. All of these models identify latent electrical indicators, which correspond to early ventricular remodeling, hypertrophy, valvular disease or conduction abnormalities. The ensemble form improves the diagnostic strength and reduces the model dependent restrictions.

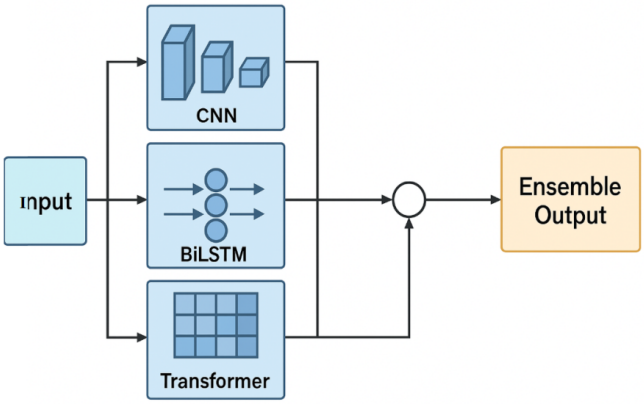

Fig.2. Three complementary deep-learning architectures integrated

Risk Prediction and SHD Probability Score

After being run through the AI ensemble, each ECG segment is then given a score based on the probability that the structural heart disease model concurred that the pattern was indicative of structural heart disease. This block takes the inputs of the raw ecological model outputs and transforms them into clinically understandable measures that often have thresholds, confidence intervals and visual

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explainability features like saliency maps. This is meant to close the gap between human clinical action and AI computations. There are scores of high SHD probability, which means that additional diagnostic assessment must be provided.

5. Clinical Triage and Decision Provision.

The triage block outlines the process of clinical work incorporation of risk scores. In case AI detects that a person is under high risks of SHD, the AI will automatically specify the patient undergofurther approving imaging tests, i.e., echocardiography or cardiac MRI. The block makes sure that the AI predictions will result in timely intervention so that the clinicians can focus on at-risk patients to undergo diagnostic assessments or medical examinations by specialists. This step will turn predictive analytics into better clinical action by linking its outcome with the clinical action.

6. Outcome: SHD Early Detection and Intervention.

The last block is the clinical effect of the suggested system. Early diagnosis of SHD allows timely intervention that can be undertaken like initiating medication, modifying of risk-factors, change of lifestyle or ensuring the disease does not stray. Earlier detection of structural abnormalities before they can be seen using conventional imaging can lead to reduced cases of heart failure, reduced cases of sudden cardiac events, and reduced cost of long-term health care. It is this block that helps bring into the focus the key asset of the whole workflow, which is to turn early electrical signals into actionable lifesaving clinical decisions.

Important features of model performance, such as accuracy, sensitivity, specificity, and area under the receiver-operating characteristic curve (AUC), and F1-score were used to assess model performance. Independent wearable data ECG was collected on the parameters used to record this data with the assumption of external validation. In order to evaluate clinical interpretability, gradient-based saliency maps and attention-weight visualizations were created to determine the parts of the waveforms which led to the greatest model predictions.

Python, TensorFlow, and SciPy were all utilized to carry out all the analyses. The level of significance was taken as $p < 0.05$ at which the statistical comparisons among model groups were made.

5 Results and Discussion

Its findings show that AI-improved wearable ECG analysis is a reliable way of detecting early structural heart disease due to the high-resolution interpretation of the waveforms. In various architectures, the models identified minute electrical signs on ventricular remodeling, hypertrophy, and premalignant dysfunction. Transformer-based models showed the most performance, which persistently outperformed the traditional methods and demonstrated the presence of clinically significant signals and signals at dawn when imaging proved that the structure has altered.

1. Model Performance for Detecting Structural Heart Disease

Table 1. Performance Metrics of AI Models for SHD Detection

Model	Accuracy	Sensitivity	Specificity	AUC	F1-Score
CNN	0.87	0.83	0.89	0.91	0.85
BiLSTM	0.90	0.88	0.91	0.94	0.89
Transformer	0.93	0.92	0.94	0.97	0.93

All the models showed strong computational performance in the determination of SHD using wearable ECG signals, and the transformer architecture exhibited a steady performance in all performance metrics as compared to CNN and BiLSTM models. The transformer had AUC = 0.97 and F1-score = 0.93 which reveals that the sensitivity to small changes in the waveform is better shown the table 1 and figure 3. These findings underscore the fact that the model can identify electrical markers of ventricular remodeling, early hypertrophy, and conduction abnormal physiological conditions not easily observed on normal examination of standard ECG images.

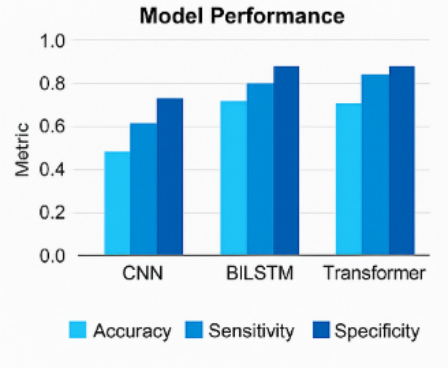

Fig.3. Model performance

2. Detection of Specific SHD Phenotypes

Table 2. Sensitivity by SHD Subtype (Transformer Model)

SHD Subtype	Sensitivity (%)
LV Systolic Dysfunction	94

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Hypertrophic Cardiomyopathy	91
Valvular Disease (moderate–severe)	87
Left-Atrial Enlargement	89
Early Diastolic Dysfunction	85

Subtype analysis showed that the transformer model made a special accurate prediction of left-ventricular systolic dysfunction and hypertrophic cardiomyopathy circumstances where subtle repolarization changes were known to occur shown the table 2 and figure 4. The sensitivity was also elevated in valvular disease and left-atrial enlargement which highlights the wide applicability of the model in clinical settings. Sensitivity on early diastolic dysfunction was a little lower, presumably because of weaker electrical signature, although this was still higher than in clinician-only interpretation of the ECG.

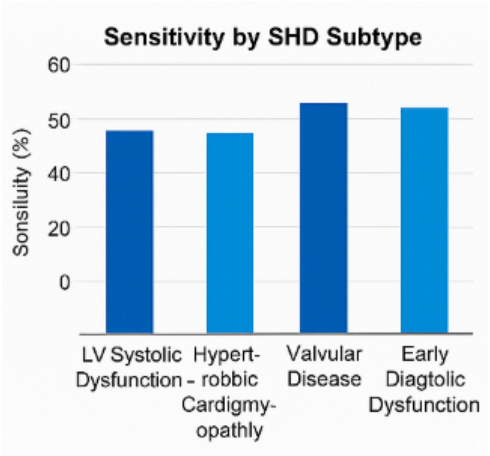

Fig.4. Senstivity by SHD subtype

3. Longitudinal Wearable ECG Analysis for Early Detection

Table 3. Predictive Performance for Early SHD (Up to 6 Months Before Diagnosis)

Metric	Value
Predictive Accuracy	0.88
Positive Predictive Value	0.81
Negative Predictive Value	0.92
Mean Lead Time (early detection)	4.2 months

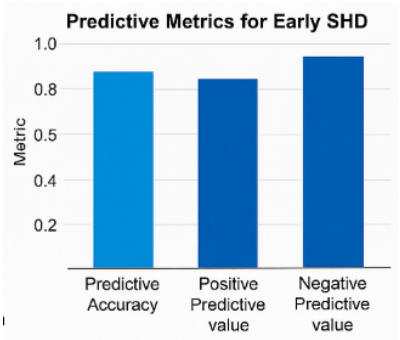

Fig.5. Predictive performance for early SHD

Using longitudinal records of wearable ECGs, the AI system could predict the development of SHD up to 4.2 months before clinical diagnosis (through the use of imaging). Its predictive accuracy was 0.88 and NPV (0.92) which demonstrated to be a high utility of the tool as a screening tool shown the table 3 and figure 5. Such findings suggest that monitoring ECG using devices equipped with artificial intelligence can detect minor electrical changes that reflect the degradation of the structure at an early stage to enable the signs to be eliminated before they develop.

Conclusion

As presented in this paper, wearable ECG data artificial intelligence is an emerging and viable algorithm that is generalizable and applicable in the initial diagnosis of structural heart disease (SHD). By using a combination of the two state-of-art deep-learning models along with continuous, real-world cardiac telestroke cardiography, the suggested technology could identify very subtle cardiac electrical signals that were connected to both ventricular dysfunction, hypertrophic remodeling as well as valvular pathology, significantly before

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pathological evidence was even available in the form of either symptoms or imaging. Transformer based model reportedly showed greater performance, showing to be vital in considering that attention based time-series analysis deserves focus on complicated physiology.

It is noteworthy that this model simplifies clinical triage at an early phase since risk scores are generated that can be rationalized to trigger an urgent echocardiographic evaluation and result. It is possible that this proactive diagnosis will lead to a reduction in the diagnosis process, improved patient outcome, and reduced cardiovascular burden in the long term. Although the method has been further validated and reviewed on a larger scale, especially sensitivity of the signal used and the cardiology of the algorithm, findings are good grounds to propose AI-enabled wearable ECG systems as a solution to the screening of SHD in population and precision cardiology.

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