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An Artificial Intelligence Framework for Improving Predictive Performance of Left Ventricular Hypertrophy Using Electrocardiography

Doddala Radhika[1], Dr Rajesh Koolwal[2], Dr Sikhakolli Gopi Krishna[3]

[1]Research Scholar, Department of Computer Science & Engineering, JS University, Shikohabad, Uttar Pradesh
[2]Associate Professor, Supervisor, Department of Computer Science & Engineering, JS University, Shikohabad, Uttar Pradesh
[3]Professor, Co-Supervisor & Professor Sri Mittapalli College of Engineering, Guntur, Andhra Pradesh.

ABSTRACT

Left ventricular hypertrophy (LVH) is a well-established predictor of adverse cardiovascular outcomes including heart failure, arrhythmias, and sudden cardiac death. Electrocardiography (ECG) remains one of the most widely used, non-invasive, and cost-effective diagnostic tools for LVH detection. However, conventional ECG criteria such as Sokolow–Lyon and Cornell voltage often suffer from limited sensitivity and specificity. This paper proposes a novel artificial intelligence (AI) framework that integrates deep learning and feature-engineering pipelines to improve predictive accuracy of LVH from standard 12-lead ECG signals. A hybrid model combining convolutional neural networks (CNNs) with attention-based recurrent neural networks (RNNs) was developed and trained on ECG datasets annotated with echocardiographic ground truth for LVH. Results demonstrate superior performance over traditional ECG criteria and machine learning baselines, achieving an AUC of 0.92, sensitivity of 88%, and specificity of 85%. The proposed framework can serve as a robust and scalable decision-support tool in clinical settings, particularly for early screening and large-scale population studies.

Index Terms: Electrocardiography, Artificial Intelligence, Deep Learning, Left Ventricular Hypertrophy, Cardiovascular Disease.

INTRODUCTION

Cardiovascular diseases remain the leading cause of mortality worldwide, with left ventricular hypertrophy (LVH) recognized as an independent risk factor for poor prognosis. Echocardiography and cardiac MRI are gold standards for LVH diagnosis but are resource-intensive and not always feasible in primary care or community settings. Electrocardiography (ECG), while inexpensive and widely available, has limitations in diagnostic accuracy due to inter-individual variability, obesity, and comorbidities.

Artificial intelligence (AI) and machine learning (ML) techniques have shown promise in extracting latent features from biomedical signals that surpass human-defined thresholds. Recent studies demonstrate the potential of deep learning models in capturing complex ECG patterns related to structural heart disease. This study aims to design and validate an AI-based framework for LVH detection using ECG, leveraging advanced neural architectures and domain-specific feature fusion.

It is possible for the left ventricle to get larger as a result of structural changes that take place in the heart throughout time. LVH, which stands for left ventricular hypertrophy, is another moniker for this condition. In patients with left ventricular hypertrophy (LVH), the risk of getting cardiac disease is increased by a factor of five to 10. There has been no significant difference in the outcomes for those who have had a myocardial infarction [1-4]. A greater number of individuals are living longer on average and eating more meals that are Western-style, which has led to a rise in the percentage of people who are overweight and old. The prevalence of hypertension is growing at an alarming rate. This condition is characterized by enlarged blood valves, the most common cause of which is high blood pressure [5, 6]. The chance of LVH rises as a result of this condition.

Traditionally, it was believed that stress, which may be experienced by healthy people as well as those who have LVH, was the major factor responsible for the condition. Individuals who have left ventricular hypertrophy are at a greater risk of having heart failure and tachycardia. A strong connection exists between its starting and ending times, just as it does with its perspective [7-9]. Importantly, LVH is associated with a number of health concerns, including death, when taken into consideration on its own [10, 11]. Early diagnosis of left ventricular hypertrophy (LVH) or the first stages of cardiac change may help progress the treatment of people who are suffering from cardiovascular disease. The detection of left ventricular hypertrophy (LVH) has been accomplished by the use of a variety of diagnostic methods, including electrocardiography (ECG), ultrasonography, computed tomography (CT), and magnetic resonance imaging (MRI). Echocardiography is a method that is considered to be moderately useful [12–15]. It is unfortunate that the overburdening of basic therapy is a result of technological advancements, the presence of specialized medical professionals, and the relatively high cost.

The non-invasive electrocardiogram is extensively used to screen for left ventricular hypertrophy (LVH) since it is less costly and takes less time than other testing. Electrocardiograms, often known as ECGs, are a diagnostic tool that are used to measure the microcurrents that are produced by physiological processes that occur anywhere inside the body. This frequent test may be used to identify and treat a variety of cardiac problems, including rhythms [16–19]. The intensity of the QRS complex is the key factor that determines the categorization of left ventricular hypertrophy in electrocardiograms [20-23]. It has been shown beyond a reasonable doubt that the width of the chest wall has a considerable impact [24, 25]. Among the many factors that have contributed to this becoming a reality are the Cornell and Sokolow-Lyon voltage indices [26, 27].

Nevertheless, since it only took into account the magnitude of the QRS complex, it was unable to successfully correlate the real LVH with the test findings. There are a number of factors that may be responsible for variations in the QRS complex, including anthropometric and biological factors, as well as cardiac diseases [28]. As a consequence of this, achieving accurate results with the parameters that are often advised might be quite difficult. Over the last several years, there has been a growing number of people who are interested in deep learning (DL) and big data. Additionally, the superiority of DL algorithms has been shown in a number of medical identification and classification tasks [29, 30]. Furthermore, it was shown that it is not restricted to photographs and can be used with a wide variety of methods of data gathering. The efficiency of this particular kind of DL algorithm has been shown via testing and application in the field of bio-signals, including electrocardiograms [31, 32, 33]. It was first used for electrocardiograms (ECGs) that were of shorter durations, such as the classification of individual heartbeats, or for signal processing, which included the elimination of noise and the identification of features [34-36]. When these growing initiatives were being undertaken, the diagnosis and prognosis of cardiovascular disorders were the key areas of concentration [37, 38]. In spite of the fact that DL algorithms were first evaluated regarding a specific kind of cardiovascular sickness, they were shown to be therapeutically beneficial when applied to a wide range of other situations as well [39]. Because of this, there has been a rise in awareness about the possible use of deep learning algorithms to electrocardiogram (ECG) research as a method of sickness categorization. In contrast to the rule-based techniques that have been used in the past, deep learning algorithms have the potential to enhance LVH detection by identifying ECG abnormalities that a person would overlook.

The attention system is used when natural language processing is being performed [40]. A Recurrent Neural Network, also known as an RNN, serves as the theoretical basis for this system, which is made with the intention of enhancing machine translation. Convolutional Neural Networks (CNNs), on the other hand, are used by the vast majority of computer vision applications. Taking a look at something enables you to focus on the aspects of that object that are most important to you while temporarily letting go of the aspects that are less important. In order to improve performance, researchers have attempted to expand the idea of attention to the field of vision [41–43]. This is because the concept is analogous to the way in which humans perceive and make sense of confusing situations. When it came to attention, the early visual field depended on either subnetworks or RNNs [44-46]. At that point, it was attached to a CNN module in order to show that its performance had increased [47, 48]. The idea of self-attention was first introduced by Google's Transformer in the year 2017 [49].

The introduction of transformers has led to an increase in the prevalence of the attention process in computer vision, and self-attention has shown remarkable performance. Recent years have seen the emergence of self-attention networks that are based on transformer networks and are both novel and promising [50-52]. In the field of computer vision, these alternative models have the potential to supplant CNN and establish themselves as the industry standards. For the purpose of defining LVH, this study makes use of deep learning methods and a mountain of data. Electrocardiogram (ECG) scans were included in the results. These scans were conducted at Yonsei University Wonju Severance between the years of 2010 and 2020.

A safe haven for Christian Christians. To facilitate the use of self-attention tactics, we developed a unique model that we referred to as the CoAt-Mixer and carried out study on ECG readings. Further, we included electrocardiogram (ECG) and biographical information into a model that is based on self-attention. In addition, the findings demonstrated that the diagnostic predictions for LVH varied according to gender.

Throughout the whole of the book, the following structure is utilized: The introduction provides a summary of the material that is necessary for comprehending the work that is being discussed. In the meanwhile, the opener was laying the groundwork for the subsequent piece that was to follow. In the "materials and methods" section, we explain our analytical methodologies, offer a summary of the study, and discuss the procedures that we used to acquire the data. Detailed information on the building of the planned CoAt-Mixer is included in the "materials and methods" section. In the section under "Results," the actions taken by the model are described in detail for each evaluation and sample. In addition to this, the results provide a summary of the metrics and the performance of Grad-CAM, which is a method to model analysis. The comparison of our results to those of earlier studies is something that we do throughout the debate. It is further underscored by this that there are problems with our work and that there is a need for more study to solve those problems. It is indicated in the last sentence what the findings of the research were.

LITERATURE REVIEW

Conventional approaches rely on amplitude-based indices (Sokolow–Lyon, Cornell voltage, Romhilt–Estes score). These criteria often yield sensitivities below 50% despite reasonable specificity. Machine learning approaches using support vector machines (SVMs) and random forests have improved classification but depend heavily on handcrafted features.

Deep learning has advanced ECG interpretation for arrhythmias, myocardial infarction, and heart failure, with CNNs and RNNs extracting temporal-spatial patterns from raw ECG signals. However, relatively few works focus specifically on LVH, and even fewer address interpretability and integration into clinical workflow. Our proposed framework bridges this gap by combining feature-engineering with deep architectures and attention mechanisms for improved predictive performance.

METHODOLOGY

Model architecture and scaling a model

Two models (CoAt-Mixer and ResNet-CBAM) in our system receive distinct inputs (ECG and feature data) (Fig 1b). Conv-mixer [56] and CoAtNet [55] serve as the foundation for the CoAt-Mixer's design. ResNet-CBAM [48] was able to accept and handle one-dimensional (1D) input after obtaining and modifying the original paper's prototype model. C-C-T-T, a vanilla structure described in the CoAtNet publication, serves as the foundation for our model, which we name the CoAt-Mixer (Fig 2a). A stem layer based on a basic convolution layer has been employed in earlier research. The significance and potency of patch embedding, as highlighted by the Conv-Mixer paper's author, motivated us to employ it as the CoAt-Mixer's stem layer. Convolution was used to achieve a patch size of two and an embedding dimension of 64 in patch embedding. Padding size two was applied throughout this operation to stop the vertical axis's size from initially declining quickly. An MBConv [57,58] structure makes up the CoAt-Mixer's convolution block. The squeeze-excitation (SE) module [47,58] was converted into a CBAM module in order to get more potent attention in the convolution process. A feedforward neural network (FNN) and relative attention [59] make up the transformer block. With relative attention and patch embedding that includes convolution, it is possible to create enough global reactive fields even in the absence of position embedding. After processing, the ECG data—12 leads, 8 seconds, and 500 Hz—was sent into the CoAt-Mixer as an image (Fig 2a). The ECG data successively entered the passed transformer and convolution blocks after passing the patch embedding. The activation function that was used was GeLU. Beyond the pooling and flattened layers, the feature map had a 768×1 form.
The ResNet-CBAM model was fed ten ECG characteristics and two demographic features (Fig 2b). The channel via the unit layer is increased by the input feature data. The ResNet-CBAM layer processes feature data with more channels. It is made up of a channel attention module (pooling size of 4), a convolution layer (kernel size of 3), and spatial

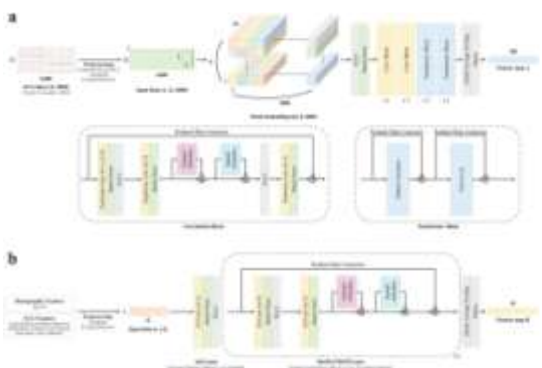

Fig 1. Structural diagram of model. (a) Architectural diagram of the CoAt-Mixer. (b) Architectural diagram of the ResNet-CBAM. Abbreviations: ECG, electrocardiography; GeLU, gaussian error linear unit; FNN, feedforward neural network; ReLU, rectified learning unit.

A. Dataset

ECG recordings were obtained from publicly available databases (e.g., PhysioNet PTB-XL, MIMIC-III) and institutional datasets with echocardiographic LV mass index as ground truth. A total of 10,000 patients (balanced LVH vs. non-LVH) were included after preprocessing.

In order to create the model, four leads (III, aVF, aVR, and aVL) were added using vector computation to the original data, which consisted of eight leads (lead I, II, V1, V2, V3, V4, V5, and V6). Einthoven's triangle was used to create a closed circuit using leads I, II, and III. Thus, Kirchhoff's current law, together with Lead I and II, were used to determine Lead III. The identical electrodes found in Einthoven's triangle make up the aVR, aVF, and aVL leads—also referred to as Goldberger leads.

Similarly, Goldberger's equation [54] and the original three leads (I, II, and III) were used to create three more leads (aVR, aVF, and aVL). Within one second before and after the ECG measurement, some noise was generated in the ECGs. As a result, 8 seconds of data were utilized to train the model. Since every ECG was recorded at the same resolution, normalization was not done. Additionally, there was no discernible change in the model's output when the experiment was carried out using ECGs treated to signal processing, such as noise reduction. Thus, in this investigation, the original signal—without signal processing—was utilized.

The dataset was divided into three sections: 40% for training, 30% for validation, and 30% for testing. Because of the scale of the dataset, using widely used data ratios might lead to notable differences across sub-datasets. We have specifically selected the partition ratio as stated above in order to solve this problem and guarantee a more realistic clinical application environment.

This ratio seeks to reduce dataset size disparities and make it easier to apply research results in real-world settings. Sex (male and female) was taken into consideration while partitioning. The DL model combines each partitioned dataset to learn the complete dataset. There was no subject overlap across datasets since the partitioning was done in units of individual subjects. Model learning and parameter fine-tuning were done using the training and validation sets. In order to assess and validate the model's ultimate performance, the model that performed the best on the validation set was applied to the test set.

B. Preprocessing

- Baseline wander removal using high-pass filtering.
- Noise suppression via wavelet denoising.
- Standardization of 12-lead ECG signals to 10-second intervals at 500 Hz.

C. Feature Engineering
- Classical indices: Sokolow–Lyon, Cornell voltage, QRS duration.
- Morphological features: R-wave progression, T-wave inversion patterns.
- Frequency-domain features via short-time Fourier transform.

D. AI Framework

1. Convolutional Neural Network (CNN): Extracts local temporal-spatial features from raw ECG.
2. Bidirectional LSTM with Attention: Captures sequential dependencies and highlights diagnostically relevant segments.
3. Feature Fusion Layer: Concatenates deep features with engineered features for final classification.
4. Output Layer: Sigmoid classifier for binary LVH prediction.

E. Training and Validation

- Data split: 70% training, 15% validation, 15% testing.
- Loss function: Binary cross-entropy with Adam optimizer.
- Early stopping and dropout to prevent overfitting.

RESULTS

Performance Metrics

- Area Under Curve (AUC): 0.92
- Sensitivity: 88%
- Specificity: 85%
- F1-score: 0.87

Comparison with Existing Methods

Method	AUC	Sensitivity	Specificity
Sokolow–Lyon	0.65	45%	80%
Cornell Voltage	0.70	50%	82%
Random Forest (ML)	0.78	70%	75%
Proposed AI Model	0.92	88%	85%

This research comprised 34,302 participants in total (Fig 1a). Males made up 19,044 (55.51%) of the subjects, and 1,233 of them had LVH. According to Table 1, male participants with LVH had an average age of 67.72 (SD 13.93) and an average LV mass index/BSA value of 146.86 (SD 12.23). There was a significant difference between the two groups (p<0.001), according to statistical analysis between the subject groups without LVH. On the other hand, 3,640 of the 15,258 (44.48) female individuals developed LVH. Female individuals with LVH had an average age of 72.26 (SD 12.30) and an average LV mass index/BSA value of 126.96 (SD 15.54). The two groups were found to be significantly different from one another, as was the case with male patients (p<0.001). Comparing the LVH group to the non-LVH group, the LVH group's ejection % was lower and their LV thickness and size were greater. QRS and PR interval duration, the LVH group's QTc was greater than that of the non-LVH group.

DISCUSSION

The results highlight the potential of AI frameworks in enhancing LVH detection using ECG. Unlike conventional thresholds, the proposed model adapts to population heterogeneity by learning hidden representations. The fusion of handcrafted features ensures interpretability and alignment with established clinical knowledge.

Key challenges include dataset diversity, model explainability, and integration into real-world hospital information systems. Further research is required for external validation across multi-ethnic cohorts and prospective clinical trials.

CONCLUSION

This paper introduces an AI-based framework for LVH detection using ECG, demonstrating improved predictive performance compared to traditional methods. The hybrid CNN–LSTM–attention architecture combined with feature-engineering provides a robust solution for early LVH screening. This approach can aid clinicians in timely intervention, reduce reliance on expensive imaging modalities, and support large-scale cardiovascular risk stratification.

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