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A Novel CNN-RNN-LSTM Framework for Predictive Cardiovascular Diagnostics of Aortic Stenosis in a Large Scale 12-Lead ECG Dataset

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Abstract:
Aortic stenosis (AS) is a disease of the valve between the heart and aorta and may lead to heart failure if left untreated; it is one of the significant valvular heart diseases caused by the narrowing of this valve. Conventional diagnostic techniques are invasive and require resources. Machine learning and deep learning approaches for the non-invasive identification of AS were investigated using an extensive 12-lead ECG dataset of 10,646 patient records. A range of models was assessed for diagnostic performance, including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), a hybrid CNN-LSTM model, and a hybrid CNN-RNN-LSTM model. The results indicate that SVM and RF had 74% and 76% accuracy, respectively, while the CNN model improved the accuracy to 80%. The accuracy of the LSTM model was 82%, and the accuracy of the CNN-LSTM hybrid model was 85%. The most proficient model was the hybrid CNN-RNN-LSTM model, which had an accuracy of 87% and high precision, recall, and F1 scores. The promise of deep learning, especially hybrid models, for advancing non-invasive diagnostic techniques for aortic stenosis, including those that could greatly aid early detection and improve patient outcomes in a clinical setting, is highlighted by this research.

Keywords: Aortic Stenosis, Convolutional Neural Network, Random Forest, Long Short-Term Memory, Support Vector Machine, 12 Lead ECG

1. Introduction

ECG is a graphic representation of voltage over time corresponding to the electrical activities accrued during the enfolding depolarisation and subsequent repolarisation of the cardiac muscle with each cardiac cycle. The ECG trace of a typical heartbeat encompasses a series of waves: a P wave, the process of atrial depolarisation; a QRS complex, ventricular depolarisation; and a T wave, ventricular repolarisation. The PR, ST and QT intervals are additional segments of the signal. Arrhythmias are a broad category of cardiac disorders manifested by abnormalities of the heart beating at an abnormal rate or rhythm. However, there is a multitude of such categories, each with a different presentation, such as sinus bradycardia (SB), atrial tachycardia (AT), premature ventricular contraction (PVC), and many other chaotic rhythms with absent or abnormal waveforms and intervals. Atrial fibrillation (AFIB) is the most prevalent and harmful type of arrhythmia and may occur with aortic stenosis at the same time. These conditions are associated with a striking increase in the risk of severe cardiac dysfunction and cerebrovascular accidents.

First, ECG data is screened and assessed according to the current diagnostic methodologies by either cardiologists or general practitioners to determine the correct diagnosis and subsequent treatment steps, including pharmacological treatments and radiofrequency catheter ablation. Nevertheless, public health initiatives related to broadening screening practices and increasing the adoption of ECG-capable wearable technology have increased the demand for increasingly precise automated diagnoses of cardiac conditions. For algorithm training, such classification techniques require massive datasets containing all possible types of conditions.

A Deep Learning Model for early diagnosis and prediction of Aortic Stenosis is a breakthrough in cardiology, leveraging the latest in artificial intelligence to meticulously parse through a vast dataset from a 12-lead electrocardiogram (ECG) database. This is the first initiative to seek a deeper understanding of arrhythmias and the mechanisms behind their relation with aortic stenosis. The goal is to raise patient outcomes substantially through improved risk assessment methodologies and personalised treatment paradigms.

This research aims to utilise the sophisticated algorithms built into deep learning to extract subtle patterns in ECG readings that could be early signals of the onset or progression of aortic stenosis. As these techniques allow for early disease detection, early detection is critical to let time-appropriate interventions and formulation of custom therapeutic strategies based on individual patient profiles. In addition, utilising clinical data alongside ECG analysis enables forming a more excellent breadth risk assessment model. This is a comprehensive approach to providing the health care providers with the means to make a clinical decision that is appropriate based on the inherent information of each patient and the evolving nature of the patient's condition.

In addition, machine learning algorithms offer great explosive powers and provide intrinsic means for adapting to incorporate new databases and learn from them. It will lead us to even more personalised treatment plans based on innovative findings in cardiovascular care that will deliver the proper intervention, ensuring that the treatment plans coordinate closely. In short, this represents a game-changing step toward an AI-driven future of cardiovascular health management and better care and outcomes for aortic stenosis patients and other disorders.

While echocardiography is by far the mainstay of diagnosis of aortic stenosis (AS), it is essential to note that electrocardiograms can provide useful indirect markers that can be useful in the diagnostic process. ECG findings commonly seen in aortic stenosis include LVH, left atrial enlargement, and various repolarisation abnormalities, all of which may indicate increased left ventricular strain of this disease.

The rich diversity of ECG patterns in a large-scale database of 12 lead ECG recordings provides a large and varied space for training a machine learning model to identify subtle abnormalities related to aortic stenosis, provided that the model is subjected to rigorous and careful training protocols that maximise its performance.

2. Literature Review

In a study of an AI-driven electrocardiogram (AI-ECG) for early identification of moderate to severe aortic valve stenosis (AS) to improve patient outcomes following aortic valve replacement procedures, Cohen-Shelly et al. (2021), An extensive dataset of 258,607 adults who had both echocardiography and ECG analysis was investigated, and 9,723 were successfully identified with moderate to severe AS. We designed and validated the AI-ECG on a cohort of 25,893 and then tested the AI-ECG on 102,926 subjects from a total of 129,788, with an area under the curve (AUC) of 0.85. However, when demographic variables like age and gender were added to the model, the sensitivity increased to 78%, specificity to 74%, and accuracy overall was maintained at 74%, with performance significantly improved (AUC of 0.90). In addition, the 15-year hazard ratios for developing moderate or severe AS were high among those with false positive results (hazard ratio 2.18). Collectively, these results suggest that AI-ECG has the potential to act as a useful screening tool for the identification of patients at risk for AS and thus represent a critical first step to enabling early intervention and management of AS.

Vaid et al. (2023) use advanced deep learning methodologies on electrocardiograms (ECGs) to help diagnose left heart valve dysfunction, specifically Aortic Stenosis (AS) and Mitral Regurgitation (MR), in this research. This was done using a retrospective cohort analysis of 617,338 ECGs and more than 120,000 echocardiograms from five medical centres affiliated with Mount Sinai. To derive the valvular condition, a Natural Language Processing (NLP) framework was used, and the deep learning models achieved an area under the receiver operating characteristic curve (AUROC) of 0.88 for MR and 0.89 for AS, indicating the great potential to improve early diagnosis of valvular disorders and to ensure accurate detection to improve patient outcomes and reduce healthcare costs.

As Zhang et al. (2024) describe this research, AI is here to transform the clinical management of aortic stenosis (AS), a complex valvular heart condition. Socioeconomic disparities are addressed, AS is identified and treated early, and a complete understanding of the disorder is achieved through data-driven risk assessments and tailored therapeutic interventions that are aware of the role of human expertise in mitigating AI’s shortcomings in healthcare decision-making.

In this investigation, Hata et al. (2020) present a novel deep learning-based approach to the automated categorisation of aortic stenosis (AS) using electrocardiogram (ECG) images. On both 12 lead and four lead ECGs, the study uses finely tuned Convolutional Neural Networks (CNNs) to highlight key ST-T characteristics identified using Grad-CAM. It shows diagnostic accuracy that matches expert assessment, suggesting that ECG may be a valuable tool for AS identification, particularly in settings where access to echocardiography is limited.

The authors of a scholarly article (Kwon et al., 2020) present a deep learning algorithm for aortic stenosis (AS) identification using electrocardiography (ECG), which is a non-invasive diagnostic technique. The proposed methodology addresses the diagnostic challenge of a prolonged asymptomatic period of AS, facilitating earlier detection and improving patient outcomes through timely medical interventions.

In the study by Ahmadi et al. (2023), a new deep-learning architecture is presented to classify the severity of aortic stenosis from two-dimensional echocardiographic data without needing Doppler measurements, which cardiologists commonly use. The model uses a transformer-based spatiotemporal framework to analyse echocardiography cine sequences independently and achieves 95.2% and 91.5% in aortic stenosis detection and 78.1% and 83.8% in severity classification on private and public datasets, respectively while overcoming the challenges of low signal to noise ratios.

Huang et al. (2024) introduce in this study an innovative deep learning architecture, Semi-supervised Multimodal Multiple-Instance Learning (SMMIL), to improve the analysis of echocardiograms for the diagnosis of aortic stenosis (AS). Integrating spectral Dopplers and 2D cine loops with labelled and unlabeled data significantly improves classification accuracy for AS severity assessment compared to conventional methods.

3. Proposed Methodology

The proposed Hybrid CNN-RNN-LSTM model for predictive diagnosis of Aortic Stenosis in a Large-Scale 12-Lead ECG Dataset is explained in this section. In this section the authors meticulously explained the various data preprocessing techniques, feature extraction mechanisms and more specifically to feature extraction (LVH) related to aortic stenosis diagnosis. Also, the authors implemented various machine learning and deep learning models to compare the accuracy of the proposed methodology.

3.1 Dataset

We created a subset from a dataset of 45,152 patient ECGs available in the Physionet platform (Zheng et al. (2020)) and investigated the use of this data. The amount of delivered voltage per analog-to-digital (A/D) bit was quantified at 4.88, and the resolution of the A/D converter was 32 bits. Amplitude was measured in microvolts for this unit. The maximum threshold was set at 32,767 and the minimum threshold at −32,768. ECG recordings were converted to WFDB format. In this WFDB format, each ECG is denoted by a pair of files: binary raw data is stored in a mat file, and a header is sent to you (also a mat file) of the same name but with the extension. The annotation details contained in the header file were lead configuration, patient age, gender and the SNOMED CT code. The original letter designations of the file ConditionNames_SNOMED-CT.xlsx corresponded with the SNOMED CT code. A comparative analysis of other datasets with the chosen is shown in Table 1.

Table 1 Comparison of Datasets

Name	Subjects	Records (length)	Sampling rate	Age	Male, n(%)	Lead, n
MIT-BIH Dataset	47	48 (30 min)	360 Hz	23–89	25 (52.08)	2
EDB Dataset	79	90 (120 min)	250 Hz	30–84	70 (88.61)	2
AHA Dataset	N/A	154 (180 min)	250 Hz	N/A	N/A	2
Proposed Dataset	10646	10646 (10 seconds)	500 Hz	4–98	5956 (55.95)	12

The proposed flow diagram is given in Figure. 1.

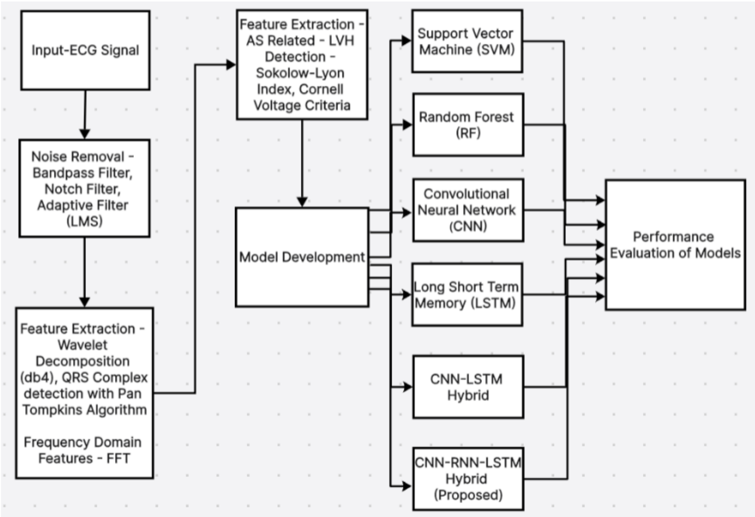

Figure. 1 Process Flow Diagram

3.2 Data Preprocessing

3.2.1 Noise Removal

ECG signals are highly vulnerable to an array of distinct types of noise, which can emanate from a multitude of diverse sources, including, but not limited to, Baseline Drift phenomena, Muscle Artifacts introduced during the acquisition process, Power Line Interference that interferes with signal integrity, Electrode Contact Noise arising from inadequate electrode adhesion, and Motion Artifacts resulting from patient movement during the recording procedure.

3.2.2 Bandpass Filter

To meticulously engineer a highly efficient bandpass filter designed explicitly for the nuanced characteristics of electrocardiogram (ECG) signals, our primary focus is a well-defined frequency spectrum encompassing the vital components of the ECG waveform, which conventionally ranges from 0.5 Hz to 45 Hz. This carefully selected frequency range is intentionally chosen due to its remarkable ability to effectively capture and represent the essential physiological signals intrinsic to the ECG while simultaneously filtering out any extraneous noise and artefacts that could compromise the accuracy and reliability of the readings we obtain. By employing such a precision-driven approach, we ensure that the resultant filter meets the stringent requirements for clinical applications and vastly enhances the clarity and integrity of the ECG signals being monitored and analysed.

3.2.3 Notch Filter

The challenge of powerline interference, which can destroy signal integrity, is addressed by a highly specialised notch filter that is intricately designed. Precisely engineered to attenuate powerline noise frequency components at 50 Hz or 60 Hz, this filter is precisely engineered to target and markedly attenuate the frequency components associated with powerline noise. The notch filter is essential in precisely isolating these frequencies and thus mitigating unwanted interference to the point where the transmitted signal is of much higher quality and clarity. By bridging two fundamental objectives, namely, reliability improvement in communication systems and maintaining data integrity, this advancement enhances the reliability of communication systems, ultimately enhancing the system's performance in many application areas.

3.2.4 Adaptive Filter (LMS)

Signal processing has long relied on adaptive filtering techniques to combat various and sometimes unpredictable sources of noise (S et al., 2024). The Least Mean Squares (LMS) algorithm is perhaps the most well-known and widely used of these techniques. Adaptive filtering is so powerful due to its ability to change continuously or adapt as the input signal changes over time. This adaption of the algorithm allows it to efficiently search and suppress noise, regardless of where it came from or how it fluctuated. The LMS algorithm continuously checks the signal and tunes the parameters corresponding to the real-time data to improve the overall quality and clarity of the desired output. The information is processed with integrity, and so the signal fidelity is improved. After applying the above filters for noise removal, figure 2 shows the resultant ECG signal.

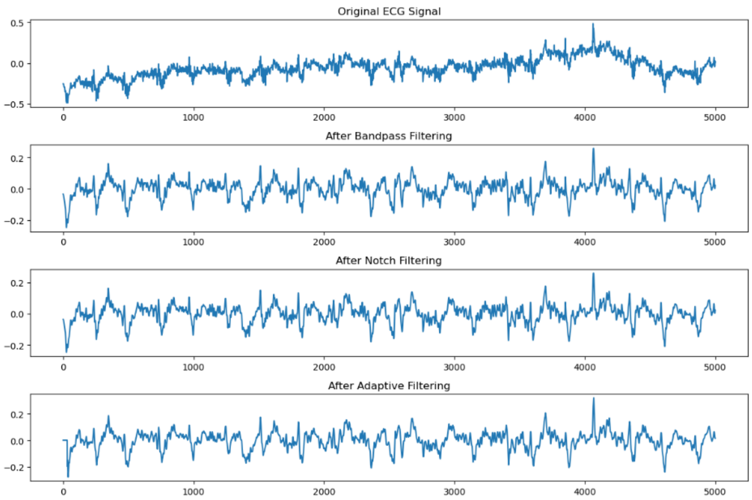

Figure. 2 Noise Removal by applying Filters

3.3 Feature Extraction

3.3.1 Wavelet Decomposition

The study shows that wavelet decomposition is essential in analysing frequency components in preprocessed ECG signals. The Daubechies wavelet (especially db4) was chosen as it was close to the QRS complex morphology needed for accurate feature extraction. It is decomposed into six levels to study its frequency components in detail. QRS complexes, peaks at high frequency (10 to 30 Hz), are important in recording and understanding heart electrical activity; P and T waves are low-frequency components, P waves are due to atrial depolarisation, and T waves to ventricular repolarisation. This analysis shows that wavelet decomposition is an effective method for ECG feature extraction and reveals the ECG signals and the underlying physiological processes.

3.3.2 Pan-Tompkins Algorithm for QRS Complex Identification

The signal is differentiated to highlight the rapid transitions of the QRS complex, which indicates ventricular depolarisation, and the analysis of electrocardiogram (ECG) signals starts. This differentiation is amplified for accurate QRS detection upon the steepest slopes. The next step is to square the differentiated signal, emphasise high-frequency components, and make the QRS complex more visible. Next, a moving window integration technique with a duration of 150 milliseconds is employed to the squared signal to smooth the signal, removing noise while preserving QRS characteristics. We then define an adaptive threshold based on the mean value of the integrated signal, scaled between 0.6 and 0.8, to detect QRS complexes effectively. This threshold is then adapted to variations in signal amplitude leading to different heart rates and physiological conditions to improve detection reliability. Finally, QRS complexes are validated because the integrated signal crosses the adaptive threshold and allows accurate ECG analysis.

3.3.3 Peak Amplitudes of the P Wave, QRS Complex, and T Wave

A segmented ECG signal can extract amplitude-based characteristics by measuring the amplitude attributes of P waves, QRS complexes, and T waves. The features provide insight into the ECG waveform morphologies and can be used to diagnose cardiac disorders. A step-by-step guide is presented for calculating these features: Peak value before the QRS complex is used to determine the P wave amplitude, the QRS complex amplitude is determined by the difference between the R peak and the minimum values at the Q or S points, and the T wave amplitude is determined by peak value after the QRS complex. The detected waves in the ECG signal are shown in Figure 3.

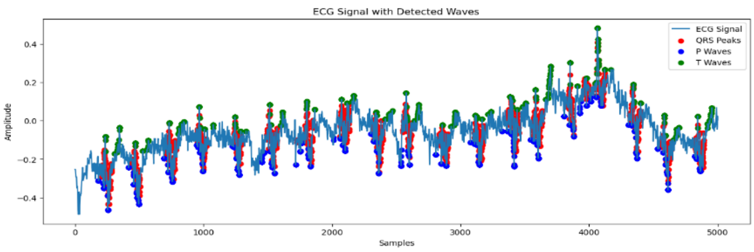

Figure. 3 Detected Waves from the ECG Signal

However, when these extracted features are used, they yield specific amplitude values for the P wave, QRS complex and T wave that can be used as foundational input for a sophisticated machine learning algorithm or can be subjected to a complete range of statistical analysis for a clinical diagnosis. Serious studies are essential to identify cardiac abnormalities, either aortic stenosis or conditions that can pressure patient health and treatment outcomes. Consequently, the design of the overall framework of cardiac diagnostics and research hinges on the thoughtful extraction and interpretation of these amplitude-based features. P_amplitude, QRS_amplitude and T_amplitude are computed by equations (1), (2), and (3), respectively.

$$P\_\text{amplitude} = \text{ECG}\left[P_{\text{peak}}\right] - \text{ECG}\left[P_{\text{start}}\right] \quad (1)$$

$$\text{QRS\_amplitude} = \text{ECG}\left[R_{\text{peak}}\right] - min\left(\text{ECG}\left[Q_{\text{point}}\right], \text{ECG}\left[S_{\text{point}}\right]\right) \quad (2)$$

$$\text{T\_amplitude} = \text{ECG}\left[T_{\text{peak}}\right] - \text{ECG}\left[T_{\text{start}}\right] \quad (3)$$

3.3.4 Frequency Domain Features

Frequency domain features play a crucial role in comprehensively understanding the spectral characteristics of electrocardiogram (ECG) signals. Using the Fourier Transform, we effectively decompose the time domain ECG signal into its constituent frequency components. We can analyse the spectral power and energy distribution across different frequency bands. This analysis is very useful for detecting and diagnosing cardiac abnormalities, such as aortic stenosis, which can show up as particular changes in the frequency spectrum of the ECG.

3.3.5 Fast Fourier Transform (FFT)

This study uses the Fast Fourier Transform (FFT) methodology to convert the electrocardiogram (ECG) signal from its original time domain representation to a more analytically advantageous frequency domain. In FFT, this transformation process provides critical insights into the amplitude characteristics of these frequency components picked out of the signal. It provides complete information on the signal’s behaviour through several frequencies. As a result, integrating both amplitude and phase data provided by the FFT provides for a much deeper and more nuanced analysis of the ECG signal, thereby enabling increased interpretations and applications in cardiovascular diagnostics such as aortic stenosis.

$$X(f) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j2\pi fn/N} \quad (4)$$

In order to extract the power spectrum, all that needs to be carried out is a detailed analysis of critical information concerning the energy distribution of signal across different frequency bands to gain a total understanding of the signal characteristics. This squared magnitude of the Fast Fourier Transform (FFT), a commonly used technique to transform the signal from the time domain to the frequency domain, hence yields more insight into the behaviour of the signal. Is this power spectrum or, mathematically speaking? With the assumption that the spectra are stationary and the energy of all frequencies is allocated at near the same ratio among all frequencies, this provides a means to infer how this energy is allocated across different frequencies and, therefore, interpret how energy is expended across different frequencies, which is essential in applications from telecommunication to the field of audio engineering to the overall understanding of the signal's underlying properties.

$$\text{Power } (f) = |X(f)|^2 \quad (5)$$

When conducting a thorough analysis of electrocardiogram (ECG) signals, it is essential to consider several pivotal frequency bands that significantly contribute to the interpretation of cardiac activity, which include the following categories:

Very Low Frequency (VLF): This frequency range is 0.0033 to 0.04 Hz, which is particularly important for understanding the heart's autonomic regulation and association with physiological and pathological states. Low Frequency (LF): This band extends from 0.04 to 0.15 Hz and is critical in reflecting the balance between sympathetic and parasympathetic nervous system influences on cardiovascular health and function. High Frequency (HF): This frequency band is predominantly due to respiratory influences on heart rate variability. Therefore, assessing the overall autonomic modulation of cardiac function and its health implications from 0.15 to 0.4 Hz is essential.

3.4 Extraction of ECG Features Related to Aortic Stenosis

3.4.1 Left Ventricular Hypertrophy (LVH)

Left ventricular hypertrophy (LVH) is an enlargement of the left ventricle, typically due to a cardiovascular disorder, such as aortic stenosis. In response to increased workload demands, the heart hypertrophies are more robust and have elevated electrical activity; this hypertrophy occurs. A narrow aortic valve means that the heart will regularly pump more blood through an increasingly thickened left ventricle that must exert more force. On an electrocardiogram (ECG), we can see that with this change, the voltage in the ECG is elevated above ordinary, meaning that the heart is working harder now. Severe complications of LVH include arrhythmias such as aortic stenosis, heart failure and increased risk of cardiovascular disease. Equations (6) and (7) show the following methods of detecting the LVH.

3.4.1.1 Sokolow-Lyon Index

This particular criterion is based on the cumulative total of the amplitudes of designated components making up the specific QRS complex, a critical part of the analysis of electrocardiograms, to gain information about cardiac electrical activity and overall heart function.

$$\text{Sokolow-Lyon Index } = S_{\mathrm{V1}} + R_{\mathrm{V5 \text{ or } V6}} \quad (6)$$

Where S_{V1} Is the S wave amplitude in lead V_1, and $R_{\mathrm{V5 \text{ or } V6}}$ is the R wave amplitude in lead V5 or V6.

Threshold:

- LVH is suggested if the index is greater than 35 mm.

3.4.1.2 Cornell Voltage Criteria

The Cornell voltage criteria combine the cumulative value of the R wave in lead aVL with the S wave in lead V3 to form a complete assessment of cardiac electrical activity.

$$\text{Cornell Voltage } = R_{\mathrm{aVL}} + S_{\mathrm{V3}} \quad (7)$$

Threshold:

- LVH is suggested if this sum is more significant than 28 mm in men and 20 mm in women.

3.4.2 QRS Duration and Amplitude

In LVH settings, a prolonged QRS duration of more than 120 ms is not uncommon and is attributed to the higher muscle mass in the left ventricle. Therefore, a prolongation of time is needed for the depolarisation process to take place effectively and efficiently.

3.4.3 Systolic and diastolic abnormalities (QRS Complex and T Waves)

Careful examination of the QRS complex and T wave patterns is done to comprehensively analyse systolic and diastolic abnormalities associated with aortic stenosis by electrocardiogram (ECG). Abnormalities in these segments of ECG reflect structural and functional changes of the heart - left ventricular hypertrophy (LVH) and delayed ventricular repolarisation due to increased strain on the left ventricle, for example. These ECG manifestations must be understood to help us gain insights into the pathophysiological mechanisms of aortic stenosis and changes in the heart.

3.4.3.1 QRS Complex

An elevation in the amplitude of the QRS complex, or an extended duration of the QRS complex, can be an important clinical indicator of left ventricular hypertrophy, a condition in which the walls of the heart’s left ventricle thicken in response to increased workload or pressure. Additionally, suppose one specifically observes systolic abnormalities in the form of notched QRS complexes. In that case, these may suggest a significant delay in conduction pathways and strain on the ventricular muscle (which may reflect ischemic injury, cardiac myopathy, and aortic stenosis).

3.4.3.2 T Wave

Absolute or asymmetric T wave deflection and decrease or inversion often indicate repolarisation abnormalities associated with ventricular strain and with the more chronic iron deficiency or ischemic events. These abnormalities are common in conditions like aortic stenosis, where the aortic valve is stiff, blood flow is obstructed, and increased heart strain is needed during relaxation. Visualisation and careful examination of these features can help to interpret systolic and diastolic abnormalities and to understand aortic stenosis and related cardiovascular problems.

3.4.3.3 QRS Duration

Longer than 120 milliseconds (the threshold) will indicate an elevation in ventricular mass that necessitates more time to adequately depolarise the heart's muscle, possibly indicating left ventricular overload or a bundle branch block.

3.4.3.4 QRS Axis

Left Axis Deviation (LAD) is when the axis is between -30° and -90° and may be due to left ventricular hypertrophy or left bundle branch block associated with ventricular overload due to aortic stenosis. A Normal Axis of -30° to +90° indicates good health and no major cardiac problems. Right Axis Deviation (RAD) with an axis greater than +90° does not represent left ventricular overload and is not associated with right ventricular disease.

4 Model Development

4.1 Support Vector Machine (SVM)

A large dataset of aortic stenosis diagnosis and detection was trained meticulously on a large scale 12 lead electrocardiogram (ECG) database using a Support Vector Machine (SVM) classifier with a radial basis function (RBF) kernel. The feature extraction process was designed to extract frequency domain characteristics and intricate signal morphology descriptors in the ECG signals. The motivation for this approach was to extract the rich information from ECG recordings to a set of hand-engineered features that could effectively represent the patterns of aortic stenosis. Although feature extraction was done with great effort and the SVM model was deployed, the results were not good in accuracy and recall. This suboptimal performance is due to the inherent complexities and high dimensionality of 12 lead ECG data. For example, conventional feature extraction techniques might not be able to express the rich, multi-faceted relationships in these datasets by extracting subtle and nuanced patterns, such as those of aortic stenosis. Moreover, since these basic methods have some limitations, there is a need to develop more advanced analytical methods to fully utilise the complexity of ECG signals to improve diagnostic accuracy for aortic stenosis, for example.

4.2 Random Forest (RF)

The Random Forest (RF) model was a modest but significant improvement over the Support Vector Machine (SVM) on a sizeable 12-lead electrocardiogram (ECG) database for diagnosing and identifying aortic stenosis. This incremental improvement is primarily because the Random Forest algorithm also has an ensemble learning approach, which is very good at capturing various features in the ECG signals. RF aggregates predictions of multiple decision trees to use different aspects of the data to build a more robust model that can handle the complexity of cardiovascular signals. Nevertheless, the Random Forest model could not overcome the severe challenges of achieving high sensitivity levels to detect aortic stenosis accurately. In particular, this cardiovascular condition presents subtle changes in the electrical signals recorded in the ECG that are very difficult to capture by models that do not exploit sequential data patterns. The ECG readings for aortic stenosis are intricate, and the temporal changes in the ECG readings are often very nuanced and, therefore, necessary for a precise diagnosis. The limitations of non-sequence-based models such as RF become evident in complex ECG datasets, where these subtle signal variations are essential. This leaves the task of achieving optimal sensitivity in detecting aortic stenosis still a complex problem, and there is a need for more sophisticated machine-learning techniques that can capture these complex signal dynamics.

4.3 Convolutional Neural Network (CNN)

A CNN model trained on raw signals from an extensive 12-lead electrocardiogram (ECG) database could accurately diagnose and detect aortic stenosis. This model was particularly good at identifying spatial features over the 12 leads of the ECG, demonstrating that it could effectively extract local patterns in ECG signals. Such spatial properties are critical to detecting abnormalities, such as aortic stenosis, which would otherwise be visually imperceptible. However, despite the CNN model's success in spatial analysis, the temporal dependencies were not well incorporated for accurate aortic stenosis detection. However, this limitation resulted in a lower recall rate than a hybrid model combining spatial and temporal analysis capabilities. ECG signals are temporal, meaning the dynamic changes in heart activity over time are essential to fully understanding cardiac conditions like aortic stenosis. Here, we identify a shortcoming of this work. Since CNN is designed to extract spatial features only, it cannot analyse temporal sequences, highlighting the need for a more hybrid architecture that combines the advantages of CNNs for spatial feature extraction with models specialised for analysing sequence data. Incorporating temporal analysis into such a hybrid model would enable it better to model the delicate temporal patterns of aortic stenosis.

4.4 Long Short-Term Memory (LSTM)

We found a standalone Long Short-Term Memory (LSTM) model promising in its ability to diagnose and detect aortic stenosis when applied to a complete 12-lead electrocardiogram (ECG) database. This model learned how the signals changed over time and demonstrated its strength by capturing the temporal patterns in the ECG signals. The LSTM model was able to model these temporal dynamics well but could not extract the spatial features of the ECG signals. This approach was limited when compared to the performance of the CNN-RNN-LSTM hybrid model. The hybrid model combines neural network architectures with convolutional and recurrent layers (specifically LSTMs). Convolutional layers in spatial feature extraction do very well and can understand and interpret the spatial relations and patterns in the ECG signals. LSTM layers also have their strength in sequential pattern learning, which means the data can be analysed across time to determine how a pattern affects it. The synergistic approach results in a more global and more robust model capable of accounting for the temporal and spatial components in the ECG signals and, at the same time, raises the diagnostic accuracy of aortic stenosis.

4.5 CNN-LSTM Hybrid Model

To make a significant advance in the quest to improve diagnostic accuracy for aortic stenosis, a large-scale 12-lead electrocardiogram (ECG) database has been used. Significant improvement over a conventional standalone convolutional neural network (CNN) and long short-term memory (LSTM) models has been achieved by a CNN-LSTM hybrid model that does not require an intermediate recurrent neural network (RNN) layer. This hybrid architecture is novel in its ability to simultaneously capture the delicate spatial patterns across the various ECG leads and appropriately model the temporal dependencies in ECG signal dynamics. Despite being a more lightweight and hybrid architecture, this hybrid has resulted in a marginal decrease in precision and recall metrics compared to higher complexity models like the CNN-RNN-LSTM. The latter framework offers a richer and more nuanced view of the data and a more complete integration of spatial and temporal features. Therefore, this more accurate model is a better diagnostic tool for clinicians trying to diagnose a patient with aortic stenosis. The results suggest a trade-off between model complexity and performance and that simpler models are beneficial but that more layers may be required to achieve optimal diagnostic outcomes in complex medical settings.

4.6 Proposed CNN-RNN-LSTM hybrid model

The CNN-RNN-LSTM hybrid model is a ground-breaking methodology in medical diagnostics. It is beneficial for aortic stenosis diagnosis from a complete 12-lead electrocardiogram (ECG) database. This model had a high accuracy rate of 87% on testing datasets and a high F1 score, and this shows that the model can be used in such an important field in healthcare. The success of this model is due to its innovative architecture, which uniquely synergistically combines Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) and Long Short Term Memories (LSTM) networks. The model can detect slight changes and characteristics of ECG signals that might be related to aortic stenosis, and CNN layers are good at extracting spatial features of ECG signals. However, the RNN and LSTM components do a great job of solving the task, which deals with the complex temporal dependencies we see in ECG data. The dual approach of this model enables it to learn subtle patterns essential for a correct diagnosis. We integrate these disparate architectures to extract fine signal features and long-range temporal information necessary for accurate aortic stenosis identification. Thus, the hybrid model has performed better than traditional machine learning methods and single architecture deep learning models in sensitivity and specificity of detection of this condition. A layered architecture is used to build the model, which produces a robust representation of the ECG signals with high recall rates and intense precision. This balance of information is essential for diagnostic reliability, especially in reducing the risk of clinical false negatives and positives. This model's ability to accurately capture delicate spatial and temporal patterns in ECG data improves its diagnostic accuracy. It suggests its potential for broader applications in medical diagnostics where high sensitivity and precision are needed. We finally demonstrate that the CNN-RNN-LSTM hybrid model is a robust diagnostic tool for aortic stenosis and can be used in the clinic for reliable detection. Its innovative design and improved performance will provide a significant step forward in cardiology and the potential for better patient outcomes through faster and more accurate diagnosis.

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5. Results and Discussions

In this considerable study, we presented an innovative hybrid model that uses the power of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short Term Memory (LSTM) networks to detect Aortic Stenosis from electrocardiogram (ECG) signals. Next, we evaluated our proposed model against various traditional machine learning algorithms and other contemporary deep learning architectures in a rigorous performance evaluation. To provide a comprehensive means of assessing the detection capability of the model, critical metrics for assessing these models were chosen to be accuracy, precision, recall, and F1-score. Each metric offers unique insights: The overall correctness of the model is called accuracy, the proportion of actual positive results to all optimistic predictions is precision, the model's ability to find all relevant instances is recall, and the F1-score is a harmonic mean of precision and recall, which is helpful in case of imbalanced datasets. The findings of this evaluation are presented systematically and organised in Table 2, where the comparative performance metrics of our CNN-RNN-LSTM hybrid model are compared with the traditional and deep learning counterparts. This detailed analysis reveals the strengths and weaknesses of each approach. It points out the advantages of combining approaches in a hybrid model for better Aortic Stenosis detection from ECG signals.

Table.2 Models Performance Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Support Vector Machine (SVM)	74	70	68	69
Random Forest (RF)	76	73	70	71
CNN	80	79	75	77
LSTM	82	80	79	79
CNN-LSTM Hybrid	85	83	82	82
Proposed CNN-RNN-LSTM Hybrid	**87**	**85**	**86**	**85.5**

The study demonstrates that deep learning models, particularly hybrid architectures, are superior for detecting Aortic Stenosis (AS) from 12-lead electrocardiogram (ECG) signals. However, traditional machine learning methods such as Support Vector Machines (SVM) and Random Forests (RF) could not handle the complicated spatial-temporal dependencies of ECG data and had only moderate performance. However, Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) based deep learning models outperformed (lacking comprehensive detection capabilities) individually. Significant accuracy improvement was achieved by introducing hybrid models, specifically CNN, CNN-RNN and CNN-RNN-LSTM hybrid models, as they can efficiently exploit spatial and temporal features of ECG signals. The confusion matrix of this is given in Figure 4.

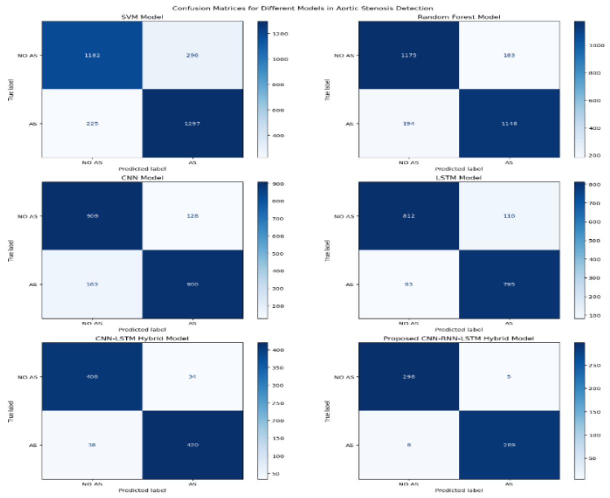

Figure. 4 Confusion Matrix of Models

On a large scale 12 lead electrocardiogram (ECG) database, various models were evaluated for detecting aortic stenosis, and we found that simpler models like SVM and RF had moderate performance but could not capture the complex ECG patterns. However, CNN and LSTM models achieved higher AUC scores because CNN can extract spatial features and LSTM can process data sequentially effectively. The hybrid CNN-LSTM model further improved these strengths. Finally, the CNN-RNN-LSTM hybrid model achieved the highest AUC. It is the best model for early detection of aortic stenosis because it can well analyse complex ECG signal patterns and temporal dependencies. Figure 5 depicts the same.

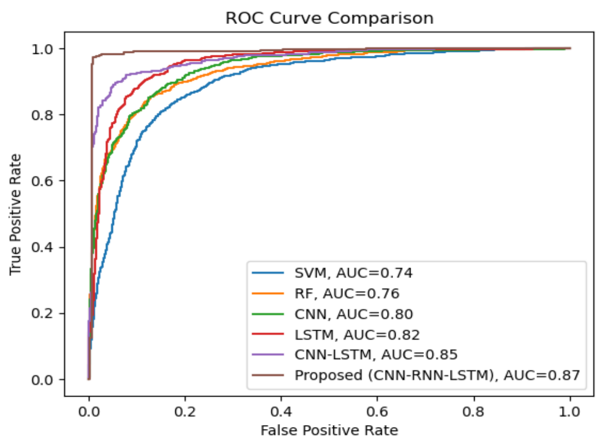

Figure. 5 ROC Curve Comparison

The analysis in Figure 6 examines the computational durations of various machine learning models and deep learning models: We implement Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), Long Short Term Memory (LSTM) networks, a CNN-LSTM hybrid model, and a proposed CNN-RNN-LSTM hybrid model. Both SVM and RF have a computational time of around 200 seconds, which is efficient for small to medium datasets, but SVM computational time can grow with large datasets because it has a quadratic optimization problem. The computational time for this CNN becomes around 220 seconds as its architecture is complex and it makes intensive operations. The complexity of LSTM networks with additional gates for managing sequential dependencies requires about 280 seconds. The CNN-LSTM hybrid model shows a reduced computational time of about 260 seconds, which shows good integration. The proposed CNN-RNN-LSTM hybrid model is shown to have the lowest time of around 170 seconds, indicating improved parallelism and optimization. Overall, non-deep learning models (SVM and RF) have moderate times, deep learning models (CNN and LSTM) are more resource intensive, and hybrid models are more efficient. This indicates that the hybrid model is a potential solution for applications that require lower computational times while preserving the advantages of the integrated neural network architectures.

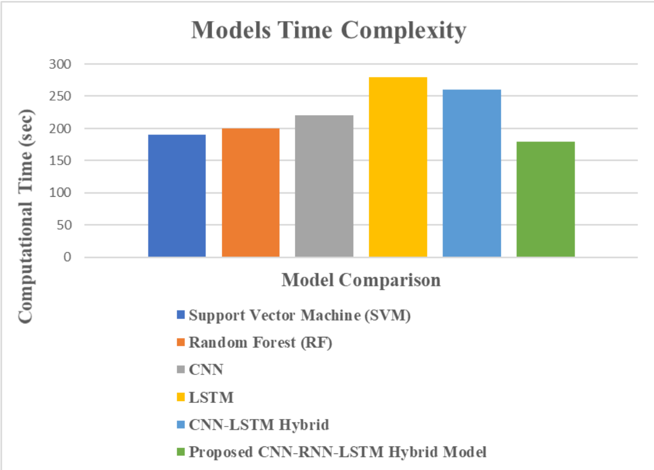

Figure. 6 Models Computational Time

6. Conclusion

A hybrid model that combines Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Long Short Term Memory (LSTM) networks is proposed for Aortic Stenosis diagnosis using a 12-lead electrocardiogram (ECG) database. The CNNs in this model extract spatial features from multi-dimensional ECG data to identify subtle patterns and anomalies necessary for Aortic Stenosis identification. ECG signals are captured by RNNs, which can capture the temporal dynamics of the ECG signals, representing the progression of cardiac conditions by changes in electrical activity over time. LSTMs handle long-range dependencies in time series data and keep information across delays or complex temporal relations. These architectures combined enhance pattern recognition and diagnostic accuracy in ECG signals. Future work will investigate hyperparameter tuning and testing on larger, more diverse datasets to make the model more robust and generalisable so that the model continues to be a valuable tool for clinicians in early detection and diagnosis, which will help improve patient outcomes.

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