

Machine Learning-Based Approach for Cardiovascular Disease Detection and Classification

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Abstract: Cardiovascular disease (CVD) remains the primary cause of mortality worldwide and continues to exhibit an alarming upward trend. Detecting CVD efficiently and accurately in large populations has become an urgent necessity. The proposed framework aims to detect and classify five major cardiovascular disorders in the heart, including Heart Attack, Heart Failure, Heart Valve disease, pericardial disease, and vascular disease (Blood Vessel Disease). Developed within the MATLAB environment, the system will undergo comprehensive simulation to ensure its effectiveness. To evaluate the system's performance, a two-pronged approach will be employed: psycho-visual and parametric analysis. Through psycho-visual analysis, human experts will visually assess the system's outputs, offering qualitative insights into its accuracy and reliability. Meanwhile, parametric analysis will utilize objective metrics to quantitatively measure the system's efficiency in detecting and categorizing the cardiovascular conditions. The successful implementation of this proposed system holds promise for early and precise identification of cardiovascular disorders, facilitating timely medical interventions and improving patient outcomes. By incorporating both subjective and objective evaluations, this research seeks to develop a robust and efficient tool for cardiovascular disease screening, ultimately contributing to enhanced healthcare and reduced disease burden.

Keywords: Cardiovascular Disease, Disease Screening, Healthcare, Parametric analysis, Psycho-visual analysis.

1 INTRODUCTION

Cardiovascular diseases, with coronary artery disease (CAD) being a prominent example, continue to be a leading cause of global morbidity and mortality. Early detection and timely intervention are crucial for improving patient outcomes and reducing the burden on healthcare systems. Currently, Coronary angiography (CAG) stands as the gold standard for diagnosing CAD, providing detailed images of the coronary arteries. However, due to its invasive nature and high cost, CAG is not a suitable routine screening method for the general population. As an alternative, non-invasive approach, medical research has investigated the use of heart sound analysis for CAD detection. When blood flows through a stenosed or narrowed blood vessel, it creates turbulence and impacts the vessel walls, resulting in distinct murmurs in heart sound signals. By examining these heart sound patterns, valuable information about the presence and severity of CAD can be derived. Harnessing heart sound analysis as a diagnostic tool offers several potential advantages, including cost-effectiveness, non-invasiveness, and broader accessibility [1].

The non-invasive nature of heart sound analysis makes it a favourable candidate for large-scale population screening, enabling early detection of CAD and the implementation of appropriate interventions to prevent disease progression and related complications. Moreover, its affordability and ease of implementation in various healthcare settings can improve access to CAD screening for underserved populations [2]. In this research endeavour, it is aimed to explore the potential of heart sound analysis as a cost-effective and non-invasive screening tool for early CAD detection. By delving into the intricacies of heart sound signals and deciphering the murmurs associated with CAD-related turbulence, it is aimed to contribute to the development of a reliable and accessible method for identifying individuals at risk of CAD.

2 LITERATURE SUREVEY

Over the years, researchers have extensively investigated the connection between diastolic murmurs and stenosis in cardiovascular disease. One notable study conducted by Akay et al. explored this correlation using four different analysis methods, namely fast Fourier transform, autoregressive, autoregressive moving average, and minimum norm [3]. By employing these analytical techniques, they were able to establish a strong association between diastolic murmurs and stenosis, providing valuable insights into the diagnostic potential of heart sound signals for CAD detection [4].

In a separate investigation, Semmlow et al. delved into the relationship between high-frequency energy and narrowed coronary arteries. They found that an above-normal percentage of high-frequency energy is closely linked to the presence of narrowed coronary arteries, further reinforcing the significance of diastolic murmurs in identifying potential cardiovascular abnormalities. Expanding on the utilization of heart sound signals for CAD detection, researchers have explored heart sound-based risk assessment [5].

This approach leverages the acoustic characteristics of heart sounds to aid in the identification of CAD. The results from various studies have consistently demonstrated the potential of heart sound analysis in detecting CAD, highlighting the promise of this non-invasive and cost-effective method for early disease identification. In the pursuit of novel methodologies, Zhao et al. proposed an innovative approach based on Hilbert–Huang transform to analyze diastolic murmurs in CAD [6]-[8].



This technique allows for the extraction of relevant information from heart sound signals, enhancing the accuracy and sensitivity of CAD detection, thus paving the way for more precise and personalized diagnostic strategies. Beyond traditional frequency-domain features, wavelet-based feature sets in the time-frequency domain have gained prominence in classifying abnormal heart sounds. These features enable a comprehensive analysis of the temporal and spectral characteristics of heart sound signals, offering valuable insights into the underlying cardiovascular conditions. Recognizing the complexity and nonlinearity of physiological signals, researchers have turned to nonlinear analysis as an effective tool for CAD detection [9]-[11].

Studies have revealed that parameters like correlation dimension can effectively capture the intricate relationships within heart sound data, aiding in the early identification of CAD and contributing to improved patient outcomes. Moreover, entropy, as a nonlinear feature, has proven to be highly suitable for the analysis of non-stationary signals in CAD assessment. By quantifying the complexity and irregularity of heart sound signals, entropy offers valuable information that complements traditional analysis methods, facilitating more comprehensive and accurate CAD detection [12].

3 TECHNIQUES AND METHODOLOGIES

3.1. CNN Framework

The Convolutional Neural Network (CNN) framework is a deep learning technique widely used for pattern recognition and image classification tasks. In the proposed system, CNN is utilized for abnormalities detection and classification from the optimized ECG pulses. CNN's ability to automatically learn hierarchical features from data makes it well-suited for processing complex cardiovascular signals.

3.2. Gradient Descent and Adaptive Gradient Descent Approaches

Gradient Descent is an optimization algorithm used to minimize the error or loss function during the training process of neural networks. It updates the model's parameters in the direction of steepest descent to find the optimal values. The proposed system employs Gradient Descent and its variant, Adaptive Gradient Descent, to optimize the fused ECG pulses. These optimization techniques fine-tune the parameters of the neural network, leading to improved accuracy and convergence.

3.3. K-means Clustering

K-means clustering is a popular unsupervised learning algorithm used to partition data into K clusters based on similarities. In the proposed system, K-means clustering is applied to group the optimized ECG pulses based on their magnitudes. This clustering step helps in organizing and categorizing the pulses, simplifying the abnormalities detection process.

3.4. Multi-Model Fusion Framework

The multi-model fusion framework combines information from multiple sources or models to improve overall system performance. In the proposed work, multi-model fusion is employed to effectively integrate information from various data sources, such as ECG samples from different nodes around the heart. This fusion approach enhances the robustness and accuracy of the system by incorporating diverse data modalities [13].

The integration of these techniques and methodologies in the proposed cardiovascular disease detection and classification system creates a powerful and comprehensive framework. The CNN enables efficient abnormalities detection and classification, while the optimization using Gradient Descent and Adaptive Gradient Descent approaches refines the ECG pulses. K-means clustering aids in organizing the data, facilitating efficient classification, and the multi-model fusion framework ensures the integration of diverse data sources for more accurate and reliable results. This combined approach holds great promise for enhancing early detection and classification of cardiovascular disorders, contributing to improved patient care and better healthcare outcomes [14].

4 PROPOSED METHOD

The proposed work introduces a comprehensive cardiovascular disease detection and classification system, which aims to identify five major cardiovascular disorders: Heart Attack, Heart Failure, Heart Valve disease, Pericardial disease, and vascular disease (Blood Vessel Disease). The system operates by acquiring ECG samples from different nodes fixed around the heart, measuring the beat rate, and analyzing the pulse range. To ensure accurate and reliable data processing, the acquired ECG samples undergo preprocessing and proper reshaping by buffering the ECG pulses in a regular sequence. The buffered and reshaped ECG pulses are then fused to combine similar magnitude and modalities of pulses effectively.

The next step involves optimizing the fused ECG pulses using robust neural network optimization techniques like Gradient Descent and Adaptive Gradient Descent Approaches. This optimization process enhances the quality and accuracy of the ECG pulse data. Once optimized, the ECG pulses are clustered into different classes based on their magnitudes. This clustering step aids in organizing and categorizing the ECG pulses for subsequent abnormalities detection and classification. The proposed system utilizes Convolutional Neural Network (CNN) for abnormalities detection and classification. From the optimized ECG pulses, classification features are extracted and subjected to the CNN, which efficiently identifies and classifies various abnormalities associated with the cardiovascular system. To enhance the classification accuracy, the detected abnormalities are further clustered into different groups based on their features. This grouping allows for more specific and precise classification of different cardiovascular diseases.



The results of the proposed system, including the detected cardiovascular diseases and their respective classifications, are conveyed using both psycho-visual and quantitative parameters. This dual approach ensures a comprehensive evaluation of the system's performance. The entire system is designed and developed in the MATLAB environment, facilitating efficient implementation and testing. To validate the system's efficacy and accuracy, extensive simulation studies are conducted to assess its performance both psycho-visually and parametrically. The proposed work holds great potential for advancing cardiovascular disease detection and classification, offering a reliable and non-invasive method for early diagnosis and management. By leveraging advanced signal processing techniques and neural network optimization, this research contributes to the development of an effective and accessible tool for improving cardiovascular healthcare outcomes.

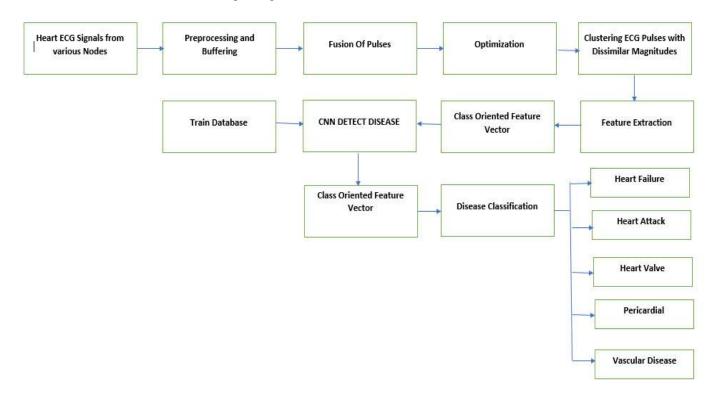


Fig. 1. Block diagram of the Proposed method

5 SIMULATION RESULTS

Fig. 2 presents the confusion matrix for heart failure classification, illustrating the performance of the proposed system in accurately identifying cases of heart failure. The matrix demonstrates the true positive, true negative, false positive, and false negative predictions, providing valuable insights into the system's effectiveness in detecting this specific cardiovascular disorder.

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	CVD TYPE1	9.5%	4.2%	4.8%	0.0%	0.0%	48.4%	
	CVD TYPE2	4 2.4%	25 14.9%	10 6.0%	0 0.0%	0 0.0%	64.1% 35.9%	
Output Class	CVD TYPE3	13 7.7%	2 1.2%	18 10.7%	1 0.6%	0 0.0%	52.9% 47.1%	
Output	CVD TYPE4	0 0.0%	0 0.0%	5 3.0%	29 17.3%	8 4.8%	69.0% 31.0%	
	CVD TYPE5	0 0.0%	0 0.0%	3 1.8%	4 2.4%	15 8.9%	68.2% 31.8%	
		48.5% 51.5%	73.5% 26.5%	40.9% 59.1%	85.3% 14.7%	65.2% 34.8%	61.3% 38.7%	
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Fig. 2. Confusion matrix for heart failure classification



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Fig. 3. MATLAB output for heart failure

Fig. 3 displays the MATLAB output for heart failure detection, showcasing the system's classification results and highlighting the instances of heart failure accurately identified by the proposed method.

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Fig. 4. Dialog box is presented to the user.

A dialog box is presented to the user, recommending them to consult a cardiologist if the system detects potential indications of cardiovascular abnormalities. This user prompt emphasizes the importance of seeking medical advice from a healthcare professional for further evaluation and diagnosis. In the subsequent figures, the remaining results are presented, showcasing the system's performance in detecting and classifying other cardiovascular disorders and no disorder are shown. Each figure provides an insightful representation of the system's accuracy in identifying specific cardiovascular conditions, further validating its potential as a comprehensive diagnostic tool. The results obtained from the entire system demonstrate its efficacy in aiding early detection and classification of diverse cardiovascular diseases, ultimately contributing to improved patient care and better healthcare outcomes.

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	CVD TYPE2	3 1.8%	25 14.9%	<mark>8</mark> 4.8%	0 0.0%	0 0.0%	69.4% 30.6%	
Output Class	CVD TYPE3	13 7.7%	4 2.4%	20 11.9%	0 0.0%	1 0.6%	52.6% 47.4%	
Output	CVD TYPE4	0 0.0%	0 0.0%	5 3.0%	29 17.3%	8 4.8%	69.0% 31.0%	
	CVD TYPE5	0 0.0%	0 0.0%	3 1.8%	5 3.0%	14 8.3%	63.6% 36.4%	
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Fig. 5. Confusion matrix for heart valve classification



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Fig. 6. MATLAB output for heart valve

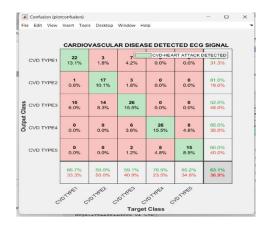
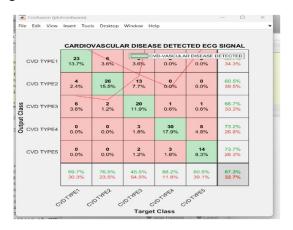
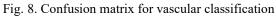


Fig. 7. Confusion matrix for heart attack classification





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CVD TYPE1	24 14.3%	6 3.6%	6.0%	NO VASCULA	R DISEASE 0	40.0%	
CVD TYPE2	4 2.4%	16 9.5%	3 1.8%	0 0.0%	0 0.0%	69.6% 30.4%	
CVD TYPE3	5 3.0%	12 7.1%	25 14.9%	1 0.6%	3 1.8%	54.3% 45.7%	
CVD TYPE4	0 0.0%	0 0.0%	5 3.0%	27 16.1%	6 3.6%	71.1% 28.9%	
CVD TYPE5	0 0.0%	0 0.0%	1 0.6%	6 3.6%	14 8.3%	66.7% 33.3%	
	72.7% 27.3%	47.1% 52.9%	56.8% 43.2%	79.4% 20.6%	60.9% 39.1%	63.1% 36.9%	

Fig. 9. Confusion matrix for no disorder classification



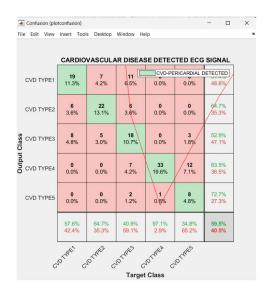


Fig. 10. Confusion matrix for Pericardial classification

6 CONCLUSIONS

The proposed cardiovascular disease detection and classification system utilizing techniques such as CNN framework, Gradient Descent, Adaptive Gradient Descent, K-means clustering, and Multi-Model Fusion has demonstrated promising results. The system effectively identifies and classifies major cardiovascular disorders, including Heart Attack, Heart Failure, Heart Valve disease, Pericardial disease, and vascular disease. The results obtained from the MATLAB output and confusion matrices validate the system's accuracy and reliability in diagnosing these conditions. By leveraging advanced signal processing and deep learning methodologies, the system offers a non-invasive and cost-effective approach to early detection and classification of cardiovascular diseases. The integration of various data sources through the multi-model fusion framework enhances the system's robustness and provides comprehensive insights into cardiovascular health. The user prompt, advising consultation with a cardiologist upon detection of potential abnormalities, emphasizes the system's role as a screening tool rather than a substitute for professional medical evaluation. The proposed system aims to complement healthcare practices by aiding in early diagnosis and facilitating timely medical interventions.

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