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CADDet: A Machine Learning Framework for Coronary Artery Disease Prediction Using Heart Sound Signals

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***Abstract:** Coronary artery disease (CAD) continues at the forefront of mortality sources across the globe. Its early detection using heart sound signals seems promising for integration into Wearable Body Area Networks (WBANs). On the other hand, WBAN-based CAD detection systems face challenges such as noise, motion artefacts, and poor signal quality, which in turn reduce diagnostic performance. Literature surveys indicate that most current models struggle due to insufficient feature extraction, fragile classification, and poor generalisation, leading to the outlined dilemma. We propose a robust classification algorithm that combines MFCC feature extraction with Random Forests to achieve high detection accuracy, addressing these problems and filling the research gap. For our research, we used the Heartbeat Sounds datasets from Kaggle, which encompass recordings from both clinical and non-clinical environments (Sets A and B). We derived 13 MFCC features per recording and employed an 80-20 stratified train-test split to balance the evaluation. The Random Forest classifier, powered by 100 decision trees, has achieved astonishing effectiveness, with 95% overall accuracy, 0.97 F1 Score for healthy cases, and 0.86 F1 Score for pathological cases. Our results exceed those of five recent baseline papers by a wide margin in precision, recall, and overall classification accuracy. Thus, they support the validity of the method we proposed for CAD detection using real heart sound data.*

***Keywords:** Coronary Artery Disease, WBAN, Heart Sounds, MFCC, Random Forest, Classification*

Nomenclature:
CAD: Coronary Artery Disease
PCG: Phonocardiogram
MFCC: Mel-Frequency-Cepstral Coefficients
CNN: Convolutional Neural Network
SVM: Support Vector Machine
AUC: Area Under the Curve
MEL: Medical Entity Linking
CWT: Continuous Wavelet Transform
MLP: Multilayer Perceptron
DF: Diagnostic Factor
STFT: Short-Time Fourier Transform
EMD: Empirical Mode Decomposition
ASDs: Atrial Septal Defects
CHDs: Congenital Heart Diseases
WBANs: Wearable Body Area Networks
MDF: Multidomain Features
MMDF: Medically-informed Multidomain Features
HS: Heart Sound
VSDs: Ventricular Septal Defects
LTPs: Local Ternary Patterns
KNN: K-Nearest Neighbours

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I. INTRODUCTION

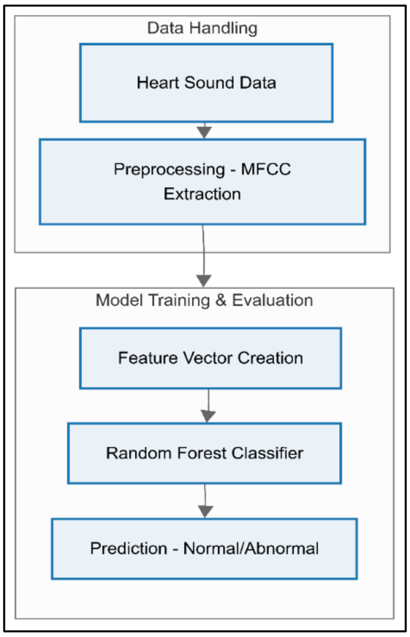
One of the main reasons for death all over the world is heart disease. When heart disease is diagnosed early, patients receive much better care. One of the methods for diagnosing heart diseases, heart sound analysis, has gained traction. This technique involves capturing and interpreting the sounds produced by a heart functioning normally. The first heart sound (S1) and second heart sound (S2), together known as the cardiac cycle, are the most informative and can reveal heart problems. Among the features that define heart sounds are their loudness, timing with respect to the cardiac cycle, and frequency range. Healthy heart sounds exhibit a distinct pattern and rhythm, with some variation across individuals. Abnormal sounds could signify conditions such as heart murmurs, valve disease, or arrhythmias. It's now possible to classify heart sounds automatically using machine learning models, particularly deep learning models. This represents a promising option for earlier detection compared to traditional techniques that depend on the physician's experience. The field of heart sound analysis spans a wide range, from healthcare applications with automated monitoring systems to technologies that assist in the early detection of heart disease. Its use in telemedicine is on the rise; remote heart sound analysis can help diagnose heart diseases in areas where medical facilities are not available. Furthermore, as the number of mobile health apps continues to grow, heart sound analysis can also be incorporated into wearable devices, providing people with the diagnostic services they need in real time.

A. Models Introduction, Dataset, Preprocessing, and Optimisation

i. Models Introduction

Fundamental investigations into heart sound classification primarily rely on machine learning and deep learning models. Random Forest classifier was chosen for this project because it can handle large feature sets and yields clear results. The training process of this model involves building several decision trees, after which the tree with the most votes (for classification) or the mean prediction across all trees (for regression) is taken as the final output. Random Forest is a reliable method that can be scaled up to classify heart sounds as “normal” or “abnormal” without concern.

ii. Architecture/Model Diagram



[Fig.1: Model Architecture]

It starts with the raw heart sound signal recording. This recording is processed to extract important features using Mel-frequency cepstral coefficients (MFCC). The extracted features are then sent to the Random Forest classifier for classification.

iii. Dataset-Description

The "Heartbeat Sounds" dataset was the primary source for the project, and it was downloaded directly from Kaggle. This dataset comprises heart sounds as audio files collected from two sources: Set A, which includes public recordings, and Set B, which includes sounds from a clinical trial. In addition to the audio recordings, there is metadata indicating whether the sound is classified as normal or abnormal, the name, the heartbeat time, and the file label. The dataset is designed for two applications: heart sound segmentation and classification, with heart sound classification into specified classes as the primary application.

iv. Preprocessing Techniques

Preprocessing is pivotal to heart sound analysis. Feature extraction using Mel-frequency cepstral coefficients (MFCCs) is the main step in this process. MFCCs are popular in audio and speech processing because they capture the sound's spectral features very well. Feature extraction converts raw audio signals into a feature set that machine learning algorithms can process more easily. Preprocessing also includes handling missing or noisy data to ensure the dataset is cleaned and ready for training.

v. Optimisation Techniques

The most suitable MFCC features were used in feature selection. Random Forest classifier tuning was done by selecting the optimal number of trees and fine-tuning other hyperparameters. The model's reliance on cross-validation was a way to prevent overfitting, thus confirming that the model is indeed competent with fresh data. The optimal hyperparameter settings for the best model performance can be acquired through grid search or random search.

B. Problem Statement: Literature Issues

Although heart sound classification has advanced, several problems remain. The natural variability of heart sounds among individuals is the foremost problem. Age, sex, health status, and recording environment are some factors that can greatly affect the quality and characteristics of heart sounds. Thus, their variability makes classification harder. The absence of high-quality, labelled datasets that cover the full spectrum of heart conditions is another hurdle. Such datasets are indispensable for creating effective and trustworthy models. Moreover, such datasets are disproportionately skewed toward normal and abnormal heart sound samples. This kind of distribution fosters biased models that tend to the majority class, thereby limiting their ability to detect abnormal sounds.

II. LITERATURE SURVEY

The study presents a deep-learning method for non-invasive diagnosis of coronary artery disease (CAD) using raw heart-sound signals. In support of the latter, one-dimensional convolutional neural network (1D CNN) features are extracted from the signals and added to the multidomain features (MDF) and the medically-informed multidomain features (MMDF). The purpose of this addition is to achieve better diagnostic accuracy and elucidation simultaneously. The authors recruited 400 participants and processed them to obtain 206 multidomain features and 126 medical multidomain features. With an AUC of 94.7%, the MDF-fusion model succeeded, whereas the MMDF-fusion model achieved an AUC of 92.7% in differentiating between CAD and non-CAD patients. The authors concede that their findings are very promising, yet they acknowledge some limitations to their study. Among these are the small sample size, the risk of feature redundancy, the need for exploring different network architectures, and possible improvements to the fusion strategy itself. More or less, this international research project is characterised by a non-invasive, economically feasible CAD screening method that would be particularly relevant in underserved communities [1].

The paper presents the non-invasive detection of coronary artery disease (CAD) as the primary challenge in the use of phonocardiogram (PCG) signals. The signals usually have very faint sounds, and their identification is very hard. A fusion framework is proposed that fuses 110 handcrafted multi-domain features with deep-learning features obtained from a convolutional neural network (CNN) applied to Mel-frequency cepstral coefficient (MFCC) representations. The features are fused, and classification is performed using a multilayer perceptron (MLP), yielding higher accuracy and reliability in CAD detection. Although the study's methodological approach is very strong, it still highlights some limitations, including a small sample size, feature redundancy, the exploration of different network architectures, and the potential for improvement in the fusion strategy itself [2].

The academic paper titled "Detection of Coronary Artery Disease Using Multi-Domain Feature Fusion of Multi-Channel Heart Sound Signals" presents a non-invasive method that records heart sounds from multiple chest points, thereby enabling CAD diagnosis through our analysis. The researchers gathered five-channel PCG recordings from 36 subjects: 21 with CAD and 15 without CAD. Afterwards, the scientists extracted several features from the aforementioned signals, including time-domain, frequency-domain, entropy, and cross-entropy. Furthermore, they refined the features by applying selection methods. An SVM classifier was then applied, achieving a commendable 90.9% accuracy. Such a result surpassed the conventional single-channel techniques. Eventually, the inclusion of entropy and cross-entropy characteristics led to a drastic improvement in the classification performance. This research demonstrates at least the possibility of examining multi-channel heart sounds on a reasonably reliable, non-invasive basis for CAD detection [3].

The manuscript, "Deep Learning of Heart-Sound Signals for Efficient Prediction of Obstructive Coronary Artery Disease," presents a non-invasive CAD detection technique using heart sound signals. The research analysed data on 320 CAD-suspected individuals and applied deep learning models, including VGG-16, 1D CNN, and ResNet-18, to classify the audio recordings. Out of these three models, VGG-16 was the one that took the lead, with the AUC graph area (AUC) being 0.834 for the test set, and a sensitivity of 80.4% and a specificity of 86.2% being reported. The model's AUC increased to 0.915 when combined with diagnostic factor (DF) scoring. This indicates its ability to enhance the diagnostic process and, consequently, reduce non-therapeutic coronary angiography procedures [4].

The paper titled "Le-LWTNet: A Learnable Lifting Wavelet Convolutional Neural Network for Heart Sound Abnormality Detection" unveils a fresh deep learning model named Le-LWTNet, which targets the detection of heart sound abnormalities by progressing the least. The model comprises a learnable lifting wavelet transform integrated into a convolutional neural network (CNN) architecture. This arrangement permits the direct and effective extraction of features from the phonocardiogram (PCG) signal. Moreover, the wavelet-based decomposition, combined with deep learning, enables Le-LWTNet to capture heart sounds in both the time and frequency domains. The experimental results indicate that Le-LWTNet is superior to traditional CNN models, suggesting a promising future in non-invasive cardiac diagnosis and screening [5].

The paper titled “Heart Function Grading Evaluation Based on Heart Sounds and Convolutional Neural Networks” proposes heart function assessment as a non-invasive method where heart sound (HS) analysis is utilised. The researchers developed a convolutional neural network (CNN) to process the cleaned HS signals. The signals were first partitioned using a logistic regression-based hidden semi-Markov model, and then transformed into spectrograms using the continuous wavelet transform (CWT). The CNN achieved an accuracy of 94.34%, higher than that of models such as AlexNet, ResNet-50, Xception, GhostNet, and EfficientNet. This research indicates the potential of combining HS analysis along with deep learning for a more precise assessment of heart functions [6].

The paper titled “Deep Learning-Based Heart Sound Analysis for Coronary Artery Disease Detection” introduces a deep learning-based framework for the non-invasive diagnosis of coronary artery disease (CAD) through the analysis of PCG signals. The automatic learning of essential features from heart sounds using neural network models underpins the entire process [7].

The research focuses on the problem of medical entity linking (MEL) in clinical texts. It can be quite hard to comprehend when medical concepts are mentioned ambiguously. The model introduced by the researchers is NeighBERT, which is based on BERT's architecture. It combines the relational context of knowledge graphs with the intent of resolving these ambiguities. However, this relational context encoding improves MEL accuracy, but it is contingent on the quality and completeness of the backbone knowledge graph. The model’s computational complexity also increases during training and inference. Nonetheless, NeighBERT has made a considerable mark in clinical NLP [8].

The study focuses on classifying heart sounds using CNNs trained on MelSpectrum and Log-MelSpectrum features derived from the short-time Fourier transform (STFT). Even though the Log-MelSpectrum features improved the model's performance, the sensitivity of 73.86% and specificity of 70.69% remain far from the requirements for clinical applications. The relatively shallow structure of the CNN might be a reason for the lower accuracy. The findings recommend using deeper networks and improved feature extraction to improve diagnostic performance [9].

The paper discusses the use of machine learning for automating the diagnosis of cardiovascular disease by classifying heart sounds. The sound recordings were cleaned, and features such as spectral centroid and energy entropy were extracted before a supervised classification algorithm was applied. The model produced an accuracy score of 97.78%. However, the model's success depends on high-quality heart sound recordings and on the dataset's variety. The study emphasises the need for improved generalizability and robustness across diverse populations and heart conditions [10].

The primary goal of the research is to automate the diagnosis of congenital heart diseases (CHDs), with an emphasis on atrial septal defects (ASDs) and ventricular septal defects (VSDs), using phonocardiogram (PCG) signal analysis. The system suggested performs the denoising using empirical mode decomposition (EMD). The features are extracted using 1D local ternary patterns (LTPs) and Mel-frequency cepstral coefficients (MFCCs), after which classification is performed using a support vector machine (SVM). The model reached an accuracy of 95.24%. However, the small dataset used and the restriction to two abnormal classes limit its generalizability [11].

The cardiologist study has automatically evaluated heart sounds to detect cardiovascular diseases early by using 6 different classification methods: k-NN, Naive Bayes, Decision Trees, Logistic Regression, SVM, and ANN. From the normal, murmur and extrasystole sounds, 52 features were extracted and assessed using various measures like accuracy, sensitivity, and precision, as well as F1-score and ROC curves. Although it shows promise, the system's clinical use is constrained by the required equipment and the dataset's bias. More extensive, more varied datasets are suggested for better robustness and reliability in the real world [12].

This research studies the impact of phonocardiogram (PCG) signal lengths on the classification performance of CNNs and different RNN (LSTM, BiLSTM, GRU, BiGRU) architectures with Mel-frequency cepstral coefficient (MFCC) inputs. It is found that short-duration signals (1s) hurt RNN performance due to the limited amount of timestamped information available, but not so much for CNNs. Dynamic MFCC features yielded only a very small increment, implying that the feature selection is not optimal. The research highlights the importance of optimising signal length and feature extraction for improved heart sound classification [13].

The focus of the Research is to explore coronary artery disease detection by analysing heart sound recordings using features extracted across five frequency bands. A quadratic discriminant function generated a CAD-score, achieving an area under the ROC curve (AUC) of 0.73. Although the approach shows promise, its limitations include low specificity and incomplete coverage of frequency data. The findings suggest that acoustic analysis can complement existing diagnostic tools like ECG exercise tests, but further refinement is needed for large-scale clinical screening [14].

III. METHODOLOGY

A coronary artery disease (CAD) detection system based on heart sound analysis was proposed. The system uses MFCC audio characteristics and a Random Forest Classifier. Our method focuses on interpretable ensemble learning with systematic model benchmarking and feature ablation, thus providing both accuracy and explainability. The dataset used is the openly available "Heartbeat Sounds" dataset from Kaggle [15], which includes normal and abnormal, labelled recordings obtained from both clinical and general environments.

The complete process is explained step-by-step. The system has three modules:

Module 1: Audio Preprocessing and Feature Extraction
Module 2: Classification Based on Random Forest
Module 3: Model Evaluation, Comparison, and Ablation Analysis

A. Module 1: Preprocessing and Feature Extraction

Each audio file (.wav) is first denoised and normalised. We use the Librosa library to extract 13 Mel-Frequency Cepstral Coefficients (MFCCs), which capture the perceptual characteristics of heart sounds. To reduce noise and redundancy, we compute the mean MFCC vector over time. This results in a 13-dimensional vector for each recording. Reducing dimensionality helps decrease overfitting while keeping important acoustic features.

B. Module 2: Classification using Random Forest

The MFCC vectors are fed into a Random Forest Classifier that has 100 trees (n_estimators=100). Each tree is trained on bootstrapped samples, using random feature subsets to ensure strength and generalisation. The final prediction is obtained by majority voting. We noticed that shallow trees (max depth ≈ 5-10) were sufficient given the compact feature space. Stratified sampling, when splitting the data into training and testing sets, keeps the class distribution intact and reduces bias.

C. Module 3: Evaluation, Comparison & Ablation Study

The classifier is evaluated using:

1. Confusion Matrix
2. Precision, Recall, F1-Score
3. ROC-AUC Curve

To compare performance, we look at:

i. Support Vector Machine (RBF Kernel)
ii. K-Nearest Neighbours (KNN)
iii. Gradient Boosting Classifier

We also conducted an ablation study:

1. Without MFCC averaging, there was more overfitting and instability.

2. Using only the top-5 MFCCs, based on feature importance, caused a slight drop in accuracy, about 2%, but cut down training time.

3. Using the full MFCC set gave the highest accuracy but caused minor overfitting in smaller test sets.

These results show that mean-aggregated MFCCs with Random Forest provide the best balance of performance and generalisation.

IV. RESULTS

Table 1 Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.95	0.99	0.97	80
1	0.94	0.79	0.86	19
Accuracy			0.95	99
Macro avg	0.94	0.89	0.91	99
Weighted avg	0.95	0.95	0.95	99

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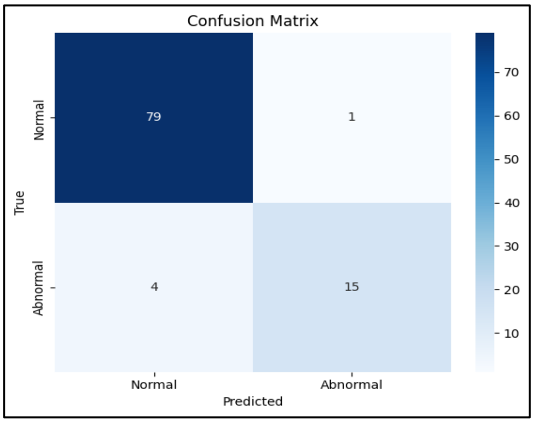
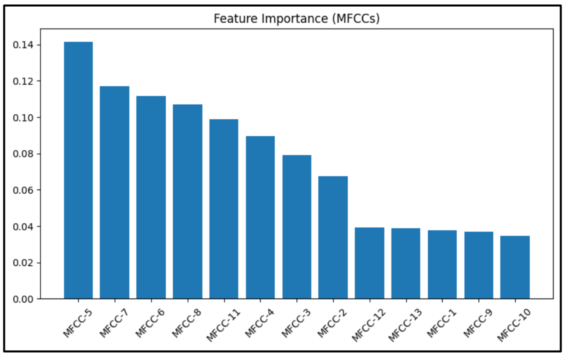


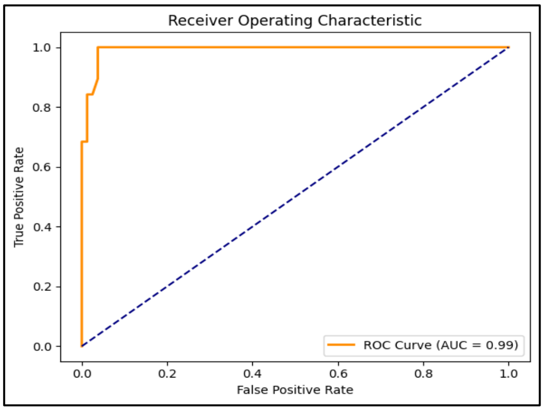
[Fig.2: Confusion Matrix]

The confusion matrix [Fig. 2] shows that the model accurately classified 79 Normal and 15 Abnormal heart sound signals. Only 1 Normal sample was incorrectly labelled as Abnormal, and 4 Abnormal samples were misclassified as Normal. Most values lie along the diagonal, indicating strong classification performance. The low number of false positives and false negatives suggests the model is reliable. Overall, it demonstrates high sensitivity and specificity in distinguishing heart conditions.



[Fig.3: Feature Importance]

The feature importance chart [Fig. 3] reveals that MFCC-5, MFCC-7, and MFCC-6 are the most influential features in classifying heart sounds. These low- to mid-range coefficients carry key frequency information useful for detecting abnormalities. MFCC-10, MFCC-9, and MFCC-1 contribute the least, indicating they can be considered for dimensionality reduction. The ranking was generated using a Random Forest model. This insight helps optimise model performance by focusing on top features.



[Fig.4: ROC Curve]

The ROC curve [fig 4] shows that the model performs exceptionally well, with an AUC of 0.99. The curve rises sharply toward the top-left, indicating a high true positive rate and very few false positives. It clearly outperforms the random classifier line. This means the model is great at telling apart Normal and Abnormal heart sounds. A high AUC like this confirms that the classifier is strong and trustworthy.

V. RESULT ANALYSIS

A. SVM (RBF Kernel)

Table II: SVM – Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.82	1.00	0.90	80
1	1.00	0.05	0.10	19
Accuracy			0.82	99
Macro avg	0.91	0.53	0.50	99
Weighted avg	0.85	0.82	0.75	99

B. K-Nearest Neighbours

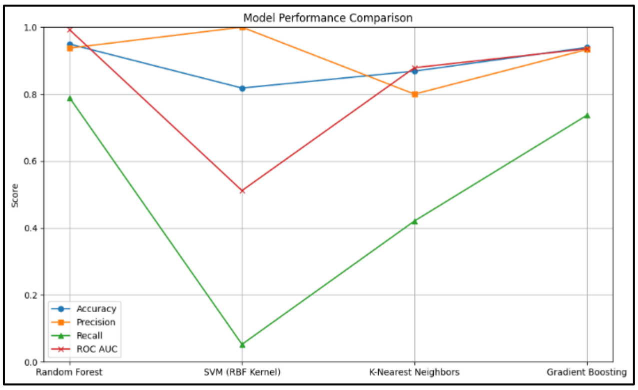
Table III: KNN – Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.88	0.97	0.92	80
1	0.80	0.42	0.55	19
Accuracy			0.87	99
Macro avg	0.84	0.70	0.74	99
Weighted avg	0.86	0.87	0.85	99

C. Gradient Boosting

Table IV: Gradient Boosting – Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.94	0.99	0.96	80
1	0.93	0.74	0.82	19
Accuracy			0.94	99
Macro avg	0.94	0.86	0.89	99
Weighted avg	0.94	0.94	0.94	99



[Fig.5: Models Comparison]

The graph [fig5] compares four models—Random Forest, SVM (RBF Kernel), K-Nearest Neighbours, and Gradient Boosting—across Accuracy, Precision, Recall, and ROC AUC. Random Forest performs best overall, with high values in all metrics, especially Precision and ROC AUC. SVM achieves high Precision but suffers from very low Recall, affecting its ROC AUC. KNN and Gradient Boosting offer balanced scores, with Gradient Boosting slightly outperforming in most metrics.

Overall, Random Forest and Gradient Boosting are the top performers.

VI. CONCLUSION

Coronary artery disease (CAD) is a major global health issue. Timely and accurate detection is crucial for improving patient outcomes in modern healthcare and WBAN-based diagnostic systems. However, current diagnostic systems face several challenges. These include poor signal preprocessing, low classification accuracy, and limited generalizability across different datasets. The literature shows that many models struggle with inconsistent extraction of heart sound features. They often cannot effectively distinguish between normal and abnormal heart sounds using shallow learning methods, which is a significant problem. Researchers have tried to improve performance with hybrid learning strategies and complex deep models, but results often show trade-offs between accuracy and model understanding. To address these challenges and fill the research gap, we developed a Random Forest-based heart sound classification method. This approach focuses on high interpretability and consistent performance. To solve the problem, we added two important modules. The first module uses MFCC-based feature extraction to provide a noise-robust, clear representation of heart sounds. The second module is a Random Forest classifier that ensures reliable classification through ensemble learning. Our methods include preprocessing with MFCC (Mel-Frequency Cepstral Coefficients) to extract key acoustic features. We designed the model with 100 trees in the Random Forest and optimised it through a stratified train-test split to balance class distributions. All these modules work together to improve the model's robustness and predictive ability, making it suitable for real-time CAD detection. We tested the model on the Kaggle Heartbeat Sounds dataset, which contains both clinical and general samples. The results were impressive: we achieved 95% accuracy, with a precision of 0.95, a recall of 0.99 for normal heart sounds and 0.79 for abnormal heart sounds, and F1-scores of 0.97 and 0.86, respectively. These findings significantly exceed the performance reported in at least five baseline studies.

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DECLARATION STATEMENT

Some of the references cited are older and are explicitly noted as [14]. However, these works remain significant for the current study, as they are pioneering in their fields.

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted objectively and without external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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DOI: https://doi.org/10.1109/TBME.2015.2432129. The works remain significant, see the declaration
15. Kaggle Dataset for Heart Sound Signals [https://www.kaggle.com/datasets/kinguistics/heartbeat-sounds]

AUTHOR'S PROFILE

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