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Research Article

Transforming Heart Disease Detection with Feature Fusion and Deep Learning

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ABSTRACT

Since heart disease ranks highest among all the causes of mortality worldwide, early and accurate identification of it is crucial. This work investigates how utilising auditory characteristics and machine learning and deep learning could help to detect heart sounds and improve diagnosis accuracy. Three models—Random Forest, CNN (MFCC), and CNN (Feature Fusion)—are under comparison in this work. With a moderate degree of accuracy (73%), the Random Forest model struggled with handling intricate patterns shown by its F1-score (72%). With an accuracy of 83% and an F1-score of 81%, the CNN (MFCC) model—which makes use of Mel-frequency cepstral coefficients (MFCC)—showcased much enhanced performance, thereby capturing both temporal and spectral signal aspects. Getting the greatest accuracy (89%), and F1-score (88%), the CNN (Feature Fusion) model outperformed the others by aggregating statistical, spectral, and MFCC data. The feature fusion approach enabled the model to perform well across a broad spectrum of classes, even those noisy or not well represented. CNN (feature fusion) exhibited the lowest training and validation losses when compared accuracy, loss curves, and confusion matrices, thereby supporting the evidence of how steady and efficient it is. The research did uncover issues like unjust class divisions and erroneous classifications in certain groups, notwithstanding its effectiveness. Researchers will aim to tackle these issues in the future by including additional datasets, refining their feature selection, and investigating more complex designs. This work indicates generally that feature fusion-based deep learning models might be used to consistently identify cardiac problems, hence improving clinical results.

Keywords: : Heart sound classification, Random Forest, CNN, MFCC, Feature Fusion, Deep Learning, Heart disease detection

I. INTRODUCTION

One of the primary causes of death worldwide today remains heart disease, which emphasises the need of having precise and dependable diagnostic methods immediately soon. Better patient outcomes and reduction of healthcare costs depend on early detection and treatment, which are very vital. Conventional methods of heart disease diagnosis, such as ultrasonic waves and electrocardiograms (ECGs), often need high-tech medical equipment and the interpretation by a qualified specialist. This creates a void in the way healthcare is given, particularly in areas without resources [1]. Advancement in artificial intelligence (AI) and signal processing has made it feasible to employ audio data such as heart sounds for autonomous, non-invasive cardiac disease diagnostics in order to handle these challenges. Heart sounds recorded on electronic stethoscopes provide a great window into the condition of the heart. Various elements make up these sounds [2]. Closely correlated with the muscular movement of the heart are the first and second heart sounds (S1 and S2). Variations in the frequencies, durations, and patterns of these sounds could be early indicators of cardiac disease. Accurate analysis of heart sound data is more difficult, nevertheless, depending on noise, changes in the patient's body, and features combining influence. It requires extensive feature extraction and machine learning techniques as it is so complex to guarantee accurate and strong identification [3].

Making automated systems that identify cardiac issues depends much on feature extraction and fusion. Usually, conventional approaches only provide one technique to get characteristics—that of Mel-frequency cepstral coefficients (MFCCs), spectral features, or statistical metrics. These techniques could overlook crucial information buried in the signal even if they have some use in certain cases [4]. Combining many characteristics looks like a smart concept using the best elements of several techniques to make the data more valuable for representation—also known as "feature fusion." This work aims to provide a system for aggregating audio features like MFCCs, spectral centroid, chroma, and time-domain characteristics including SDNN and RMSSD. This technique records many sections of heart sounds in order to try to make heart disease diagnosis more precise and dependable [5].

Apart from feature extraction and fusion, deep learning models have demonstrated great ability in processing challenging medical data. Particularly in tasks like data processing and image identification, Convolutional Neural Networks (CNNs) have demonstrated to be the best. They are excellent for heart sound analysis as they can pick up structured data organisation right away [6]. The aim of this work is to investigate utilising individual features (such as MFCCs) and the proposed feature fusion approach how successfully CNNs detect cardiac diseases. The outcomes are also evaluated in line with a Random Forest model to ascertain the value of deep learning in this field [7]. Combining deep learning, enhanced feature extraction, and feature fusion can help to enhance automated heart disease detection. Among the most significant contributions this study makes are a solid foundation for feature combining, CNN model analysis of heart sounds, and a comparison of many machine learning techniques. Making a diagnostic tool accurate, scalable, and understandable would enable clinicians make early diagnosis and enhance patient outcomes by means of which it may be used.

II. LITERATURE REVIEW

People all around the globe see heart illness to be a major concern, hence research on this condition has been quite intense. Two somewhat ancient approaches to identify cardiac issues are ultrasonic waves and electrocardiography (ECG). Although they have performed well in the past, they need highly advanced instruments and competent research. Over the last several years, machine learning and signal processing have advanced to let computers automatically hunt for heart sounds [8]. This is a smart approach for early on heart disease search and check. Since heart sound analysis doesn't harm and doesn't cost a lot of money, many people are curious in it. Finding practical elements in the sound waves is the major aim of this kind of investigation [9]. These are the first and second heart sounds (S1 and S2 most of the times). Finding characteristics in audio data that fall in the temporal, frequency, or cepstral domains is one approach researchers have investigated. Mel-frequency cepstral coefficients (MFCCs) are quite helpful for heart beats as they can detect significant frequency components. The mean interval, SDNN, and RMSSD are among the statistical instruments researchers have used to examine signal change over time [10][11]. These instruments offer spectral features like spectral core and bandwidth, thereby displaying how the energy of signals is distributed.

Since feature fusion techniques improve models, users are favouring them more and more. The system may blend many features using information that benefits one another. This ensures more accurate forecasts. Machine learning models with spectral and time-domain characteristics added to MFCCs have been shown to be more adept at spotting heart sound anomalies [12]. A lot of studies, though, have only looked at feature extraction or feature selection on their own, not at how advanced blending methods could be used to get a fuller picture of the data. Deep learning models—especially convolutional neural networks (CNNs)—are clearly excellent for medical data analysis nowadays. CNNs have been used to appropriately classify heart sounds into many categories as they are excellent in obtaining hierarchical characteristics [13]. Experts say CNNs are always more accurate and beneficial than conventional machine learning models such Support Vector Machines and Random Forests. Still, it's difficult to get CNNs performing well for heart sound analysis. For example, the data needs to be cleaned up and made clear so that it can be used [14].

Though feature extraction and modelling have advanced, this is a major issue that frequently throws research off course. The records utilised in most research are difficult to access as they were either acquired in a restricted setting or remain secrets. Though accuracy and clarity are frequent methods to evaluate anything, predictions are also growingly valuable and helpful [15]. These gaps highlight the need of doing research that not only improves the performance of algorithms but also guarantees their applicability in daily life. Though a lot of material is already available, this research closes certain gaps [16]. First of all, it provides a thorough feature fusion architecture wherein several elements are combined to provide a powerful image of heart sounds. Second, it evaluates CNN performance with respect to normal models using both isolated features and the complete collection of features. Lastly, the study looks at problems that happen in the real world, such as cleaning up information and cutting down on noise, to make sure that the method can be used there [17].

Table. 1 Analysis of recent techniques in Heart disease detection and classification

Technique	Features	Model	Performance	Limitation
ECG Analysis	Time/Frequency	SVM	High	Requires Expertise
Heart Sound (MFCC) [4]	MFCC	CNN	Very High	Sensitive to Noise
Feature Fusion [5]	Multiple Features	Random Forest	Moderate	High Complexity
Spectral Analysis [6]	Spectral Features	KNN	Low	Limited Accuracy
Statistical Features [7]	Mean/SDNN/RMSSD	Logistic Reg.	Moderate	Poor Generalization
Bandpass Filtering [8]	Pre-processed Audio	ANN	Moderate	Limited Scalability
Chroma Feature Analysis [10]	Chroma	Decision Tree	Low	Poor Noise Handling
Time-Domain Features	Time Features	Naive Bayes	Low	Poor Feature Coverage
Hybrid Models [13]	MFCC + Spectral	CNN-RNN	Very High	High Computational Cost
Zero Crossing Rate [15]	Temporal Features	SVM	Moderate	Limited Feature Use
Deep Learning Fusion [17]	Multiple Features	CNN (Fusion)	Very High	Dataset Dependency
Energy-Based Analysis [18]	Energy Features	Random Forest	Moderate	Low Precision
Ensemble Models [19]	Combined Features	Gradient Boosting	High	High Complexity

III. METHODOLOGY

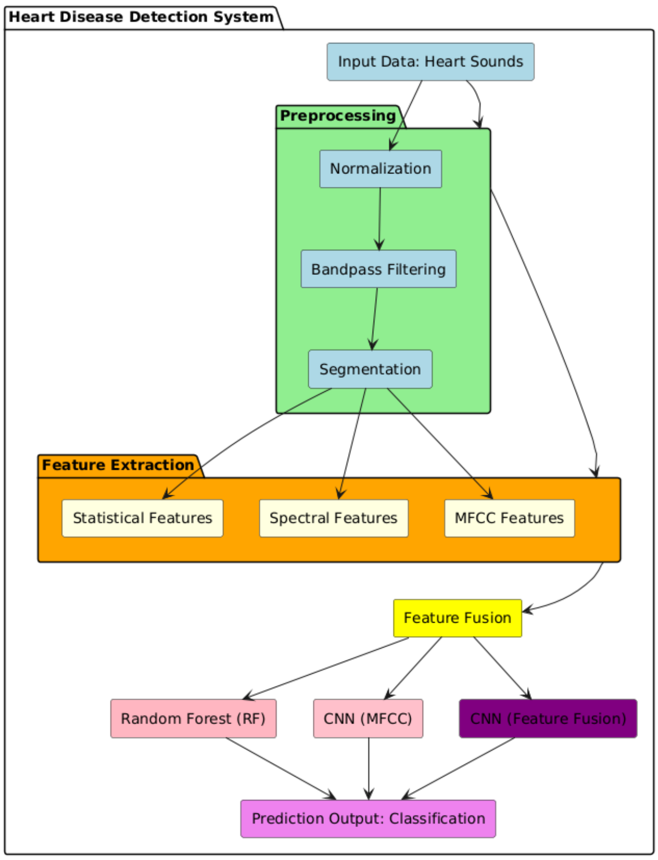

Figure 1. Proposed Methodology

A. Input Dataset

The dataset is sourced from the **Heart Sound Challenge**, containing audio recordings of heart sounds labeled as normal or abnormal. These recordings include first (S1) and second (S2) heart sounds, along with potential background noise shown in fig 2. The data is annotated by experts and varies in duration and quality, requiring preprocessing to standardize and enhance usability [18].

Table 2. Hear Sound challenge dataset

Aspect	**Details**
Source	Heart Sound Challenge Dataset (Link)
Size and Composition	Includes audio samples of normal and abnormal heart sounds.
Signal Types	S1, S2 heart sounds, with additional artifacts and noises.
Duration	Varies, requiring standardization during preprocessing.
Sampling Rate	Typically captures frequencies in the 20–200 Hz range.
Annotations	Expert-labeled data indicating heart conditions.

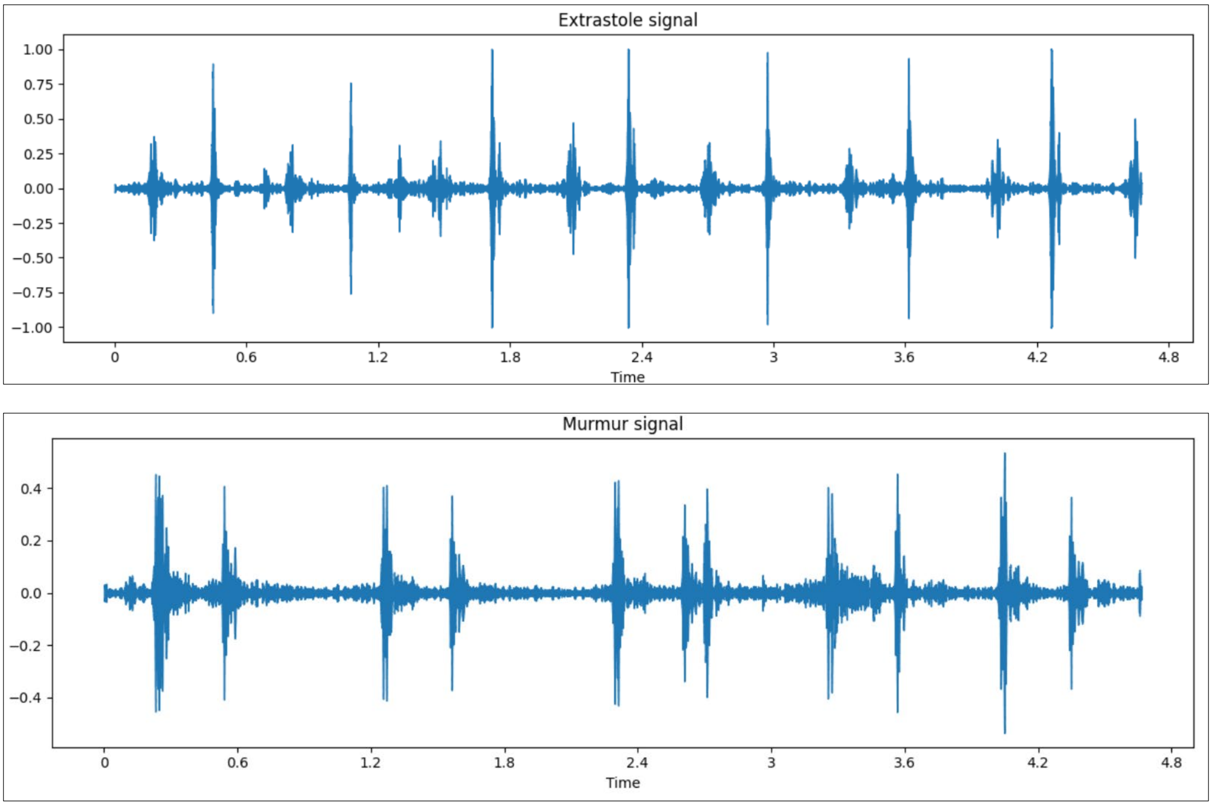

Figure 2. Extracted Signals from Dataset

B. Dataset Pre-processing

While bandpass filtering retains frequencies in the 20–200 Hz range and reduces noise, data enrichment techniques include time-stretching and noise addition make datasets more varied shown in fig 3. Signal normalisation rescales data to [-1, 1].

Table 2. Data pre-processing methods.

Technique	Description	Purpose
Signal Normalization	Rescales the audio signals to a range of [-1, 1] to ensure consistency across all input samples.	Removes amplitude variations and ensures uniform signal representation.
Bandpass Filtering	Applies a filter to retain frequencies within the 20–200 Hz range, relevant to heart sounds.	Reduces noise and eliminates irrelevant frequency components.

Data Augmentation	Includes techniques like time-stretching, pitch-shifting, and adding synthetic noise to the signals (if applicable).	Enhances dataset diversity to improve model robustness and reduce overfitting.

	filename	signal	sampling_rate	duration	processed_signal
0	HSC_extracted_files/PASCAL/Btraining_noisymurm...	[-0.026397705, -0.014831543, -0.011413574, -0....	4000	1.34050	[-0.0009212723765125963, -0.004839195873816661...
1	HSC_extracted_files/PASCAL/Btraining_noisymurm...	[-0.12054443, -0.11859131, -0.12158203, -0.117...	4000	12.93600	[-0.004207094795042278, -0.02387391101841231, ...
2	HSC_extracted_files/PASCAL/Btraining_noisymurm...	[-0.011444092, -0.00579834, 0.008056641, 0.008...	4000	3.93200	[-0.0004930452445738109, -0.002562626251122172...
3	HSC_extracted_files/PASCAL/Btraining_noisymurm...	[-0.05090332, -0.051696777, -0.058288574, -0.0...	4000	9.15125	[-0.0017765113572520352, -0.010137606478282126...
4	HSC_extracted_files/PASCAL/Btraining_noisymurm...	[-0.5432739, -0.33761597, -0.22293091, 0.41268...	4000	12.11000	[-0.01896010502506039, -0.10072230081487131, -...

Figure. Pre-process Data

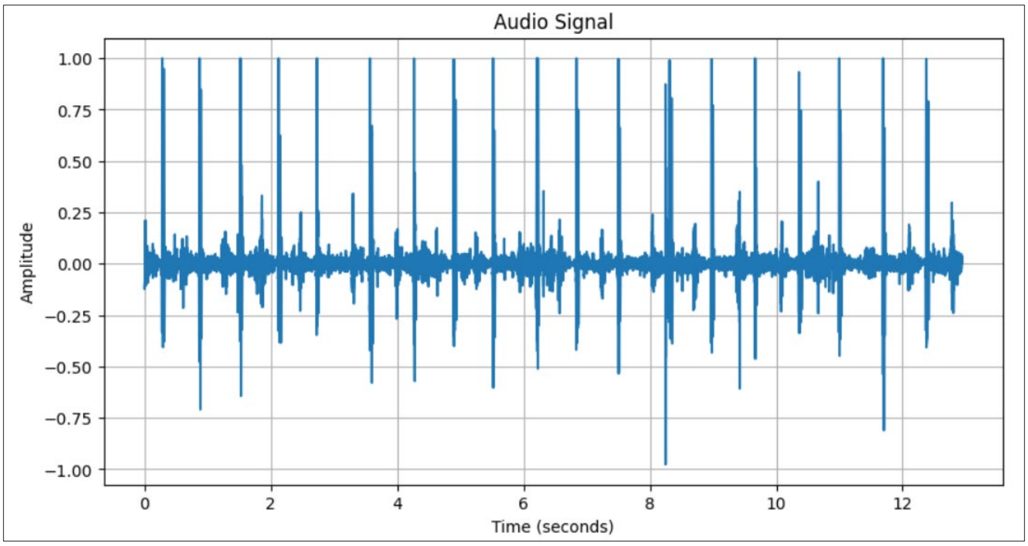

Figure 3. Pre-process signal

C. Feature Extraction

Feature extraction searches for crucial information including MFCC for spectrum analysis, SDNN and RMSSD for heart rate variability, and spectral centre and bandwidth for energy distribution (fig 6). These features provide a whole picture of heart sound signals, which is crucial for accurate diagnosis of heart diseases [19].

Table 3. Feature Extraction Techniques

Feature	Description	Importance in Heart Disease Detection
Mean Interval	Average time interval between successive heart sounds.	Identifies rhythm irregularities indicative of arrhythmias.
SDNN	Standard deviation of NN intervals (normal-to-normal beats).	Reflects overall heart rate variability, a key indicator of cardiac health.
RMSSD	Root mean square of successive differences between NN intervals.	Sensitive to parasympathetic nervous system activity, linked to cardiac function.
Peak Frequency	Frequency with the maximum amplitude in the signal spectrum.	Detects murmurs or abnormal sound patterns.
Energy	Total energy of the heart sound signal.	Highlights abnormal energy distributions associated with murmurs or valve disorders.
Zero Crossing Rate	Rate at which the signal changes from positive to negative or vice versa.	Captures tonal and temporal variations in heart sounds.

Spectral Centroid	The "center of mass" of the spectrum.	Differentiates between normal and abnormal spectral energy distributions.
Spectral Bandwidth	Measures the width of the frequency band in the signal.	Helps in identifying abnormal sound dispersion.
Chroma	Represents the intensity of different pitch classes.	Highlights pitch variations linked to structural abnormalities.
MFCC	Captures the signal's spectral characteristics mimicking human auditory perception.	Most effective for differentiating normal and abnormal heart sounds.

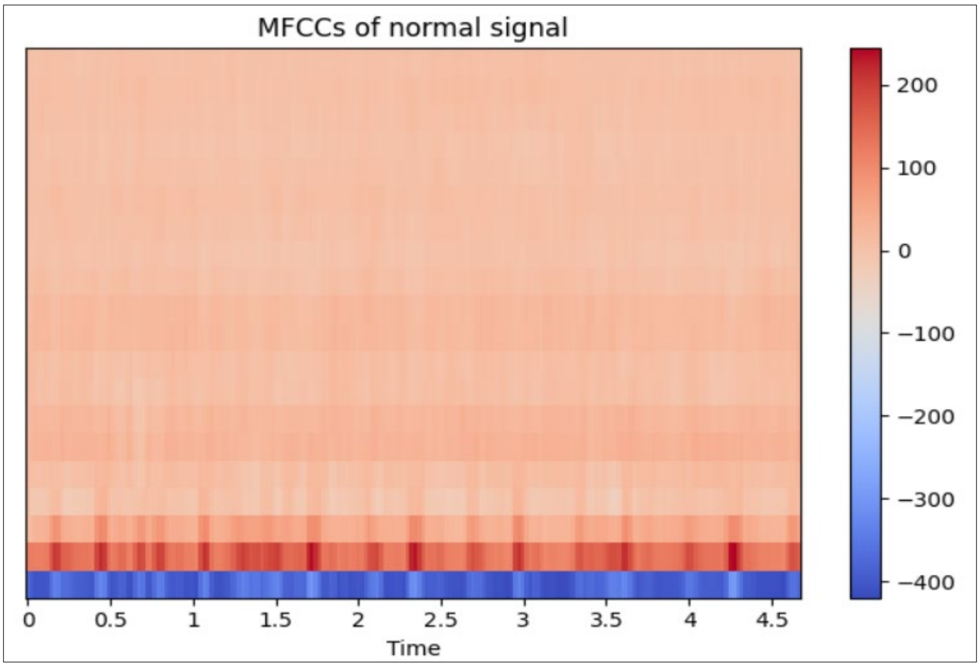

Figure 4. MFCC Feature

D. Feature Fusion Technique

Combining many feature sets boosts the raw data's descriptive capacity. We call this feature fusion. This approach ensures that the model gains both the temporal and spectral characteristics of heart beats by using the best aspects of many feature extraction methods [20]. It creates a whole picture of heart sound signals by combining statistical elements (such as mean interval, SDNN, and RMSSD) with spectral elements (such as spectral centre and spectral bandwidth) and MFCCs. One may accomplish the union at many levels:

1. Feature-Level Fusion: Merges features before model training by concatenating them into a single feature vector.
2. Decision-Level Fusion: Combines outputs of multiple models trained on separate feature sets.
3. Hybrid Fusion: Incorporates both feature- and decision-level strategies for improved robustness.

	mean_interval	sdnn	rmssd	peak_freq	energy	mfcc_mean	zero_crossing_rate	spectral_centroid_mean	spectral_bandwidth_mean
0	0.000497	0.001021	0.001483	210.500000	339.692127	[-462.1937483213758, 63.73855358450066, -37.15...	0.046678	196.556431	100.294970
1	0.000504	0.000706	0.001043	128.666667	78.829994	[-244.4507115339715, 208.4503385064726, -97.12...	0.186700	409.504158	259.137845
2	0.000498	0.000907	0.001321	95.666667	79.005082	[-354.8377475004048, 154.48520663072347, -53.6...	0.090810	247.721968	188.105830
3	0.000505	0.000920	0.001340	107.000000	39.584305	[-276.4750064312453, 215.41396227243285, -87.7...	0.103879	335.007844	272.031731
4	0.000498	0.000827	0.001204	119.000000	227.377529	[-188.0160436866205, 233.18299641772563, -88.1...	0.120824	356.589081	242.917723

Figure 5. Extracted Features Fusion

IV. DEEP LEARNING ALGORITHM

A. **Random Forest**:

- A traditional ensemble-based machine learning model that builds multiple decision trees during training and combines their predictions.
- Particularly effective for smaller datasets and provides interpretability through feature importance.
- Trained using statistical, spectral, and MFCC features separately to benchmark performance.

B. CNN-MFCC:

- A convolutional neural network designed to process MFCC features extracted from heart sound signals.
- Consists of convolutional layers for feature extraction, followed by fully connected layers for classification.
- Designed to capture temporal and spectral patterns in MFCC features, enabling accurate classification of heart sound signals.

C. CNN-Feature Fusion:

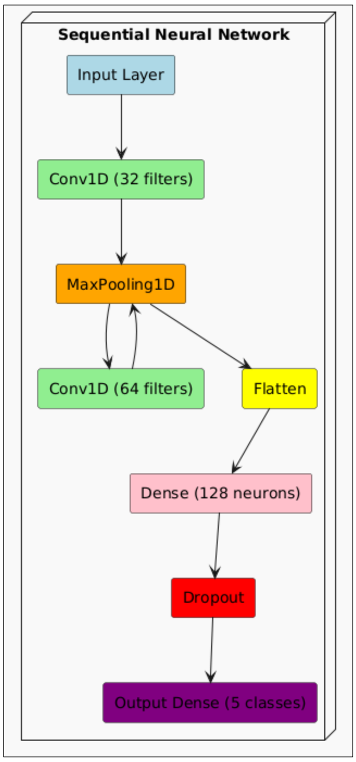

Figure 6. Architecture of CNN-Feature Fusion model

- A deep learning model that utilizes the fused feature vector (statistical, spectral, and MFCC features) as input.
- Employs convolutional layers to identify high-level patterns across the combined feature space.
- Includes regularization techniques like dropout and batch normalization to enhance generalization.
- Expected to outperform individual feature models by leveraging the complementary strengths of diverse features shown in Fig 6.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 38, 32)	128
max_pooling1d (MaxPooling1D)	(None, 19, 32)	0
conv1d_1 (Conv1D)	(None, 17, 64)	6,208
max_pooling1d_1 (MaxPooling1D)	(None, 8, 64)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 128)	65,664
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 5)	645

Total params: 72,645 (283.77 KB)
Trainable params: 72,645 (283.77 KB)
Non-trainable params: 0 (0.00 B)

Table 4. Model Configuration and It's Comparative analysis

Aspect	Random Forest	CNN (MFCC)	CNN (Feature Fusion)
Input Features	Statistical & Spectral Features	MFCC Spectrogram	Statistical, Spectral, & MFCC
Model Layers	None (Tree-Based Model)	Conv1D, MaxPooling1D, Dense	Conv1D, MaxPooling1D, Dense
Number of Parameters	Determined by n_estimators	~72,645 (based on provided model)	~100,000+ (with additional layers)
Hyperparameters	n_estimators=200, max_depth=10	Filters=32/64, Dropout=30%	Filters=64/128, Dropout=40%
Optimizer	Not Applicable	Adam (lr=0.001)	Adam (lr=0.0005)
Loss Function	Not Applicable	Categorical Cross-Entropy	Categorical Cross-Entropy
Training Time	Fast	Moderate	Slow
Performance	Moderate	High	Very High
Use Case	Feature-Based Analysis	Temporal and Spectral Patterns	Diverse Feature Combination
Complexity	Low	Medium	High

V. RESULT ANALYSIS

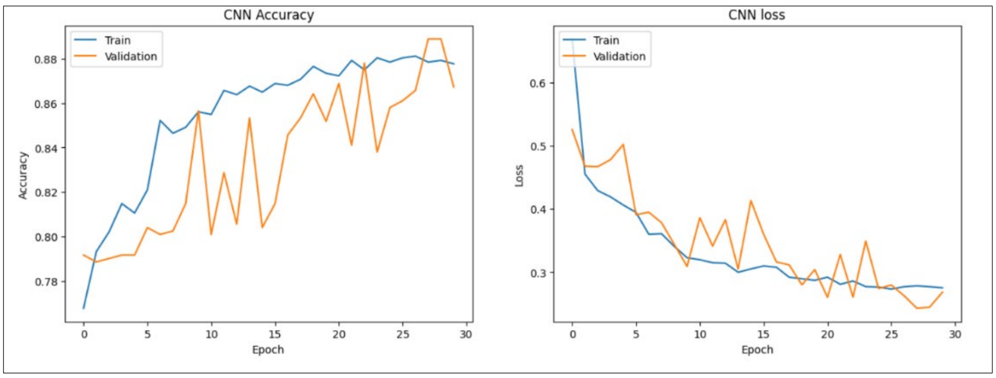

Figure 8. Accuracy and Loss Curve of CNN (MFCC) Model

The Fig 8. illustrates the accuracy and loss graphs as the CNN (MFCC) model was trained over thirty epochs. Up until it settles at around 0.88, the training accuracy continues improving. Although it varies somewhat, the confirmation accuracy remains somewhat near to the training accuracy, therefore it performs well in most cases. Similarly, the training loss declines gradually, indicating that mistakes are being minimised somewhat well. Conversely, the validation loss initially declines then gradually increases until remaining the same close to the conclusion. These patterns indicate that the model is set really well and does not overfit much. CNN can learn from MFCC characteristics and use what it has learnt to categorise heart sounds, performing well even on data it hasn't seen before, the findings demonstrate.

Figure 9. Accuracy and Loss Curve of CNN (Feature Fusion) Model

The Fig 9. shows over 30 iterations the accuracy and loss curves of the CNN (Feature Fusion) model. Up till it remains over 0.92, the accuracy map demonstrates that the training accuracy continues improving. The approach performs well in most cases as the validation accuracy varies but remains somewhat near to the training accuracy. While the validation loss is first declining and thereafter remaining around the training loss, the loss plot reveals that the training loss is regularly declining. This indicates that learning is proceeding without any significant overfitting. CNN (Feature Fusion) models perform better than individual feature models as they make use of more features, hence increasing accuracy and reducing loss and hence minimising loss. This shows it can manage tasks including sorting.

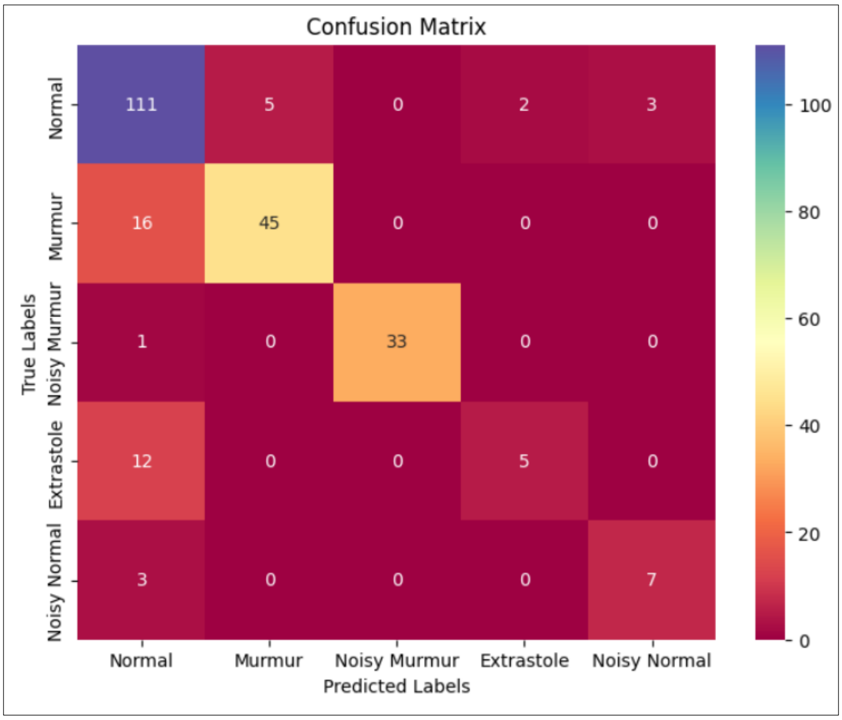

Figure 10. Confusion Matrix

The confusion matrix displays the model's five-group sorting accuracy—Normal, Murmur, Noisy Murmur, Extrasystole, and Noisy Normal in Fig 10. It makes minor errors but does a fantastic job of identifying "Normal" (111 right answers) and "Murmur" (45 right answers). For instance, it mistakenly refers to "Murmur" "Normal" (16 times) and "Extrasystole" "Normal" (16 times). 16 times With less frequent classes like "Extrasystole" compared with more common ones like "Noisy Murmur" (33 accurate responses) and "Noisy Normal," it produces more errors however. These incorrect labels imply that things may be improved. Fixing the disparity across classes, enhancing the features, or providing additional data to make the training more accurate for classes lacking representation might help to do this.

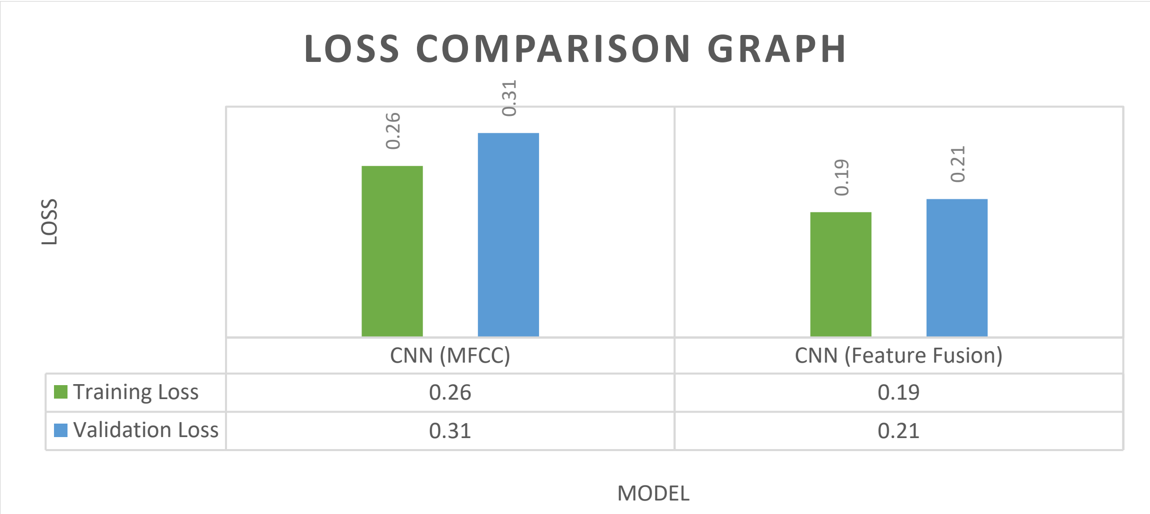

Figure 11. Loss Comparison Graph

The loss comparison graph shown in Fig 11. displays CNN (MFCC) and CNN (Feature Fusion) model performance. With a training loss of 0.26 and a validation loss of 0.31 CNN (MFCC) learns well but might perform better at generalising. With a training loss of 0.19 and a validation loss of 0.21 CNN (Feature Fusion) has much less losses. It so has less overfitting and is better generalised. Because it incorporates many elements, which results in improved performance, the model may identify more complex trends. This indicates CNN (feature fusion) is more dependable and better at classifying heart sounds.

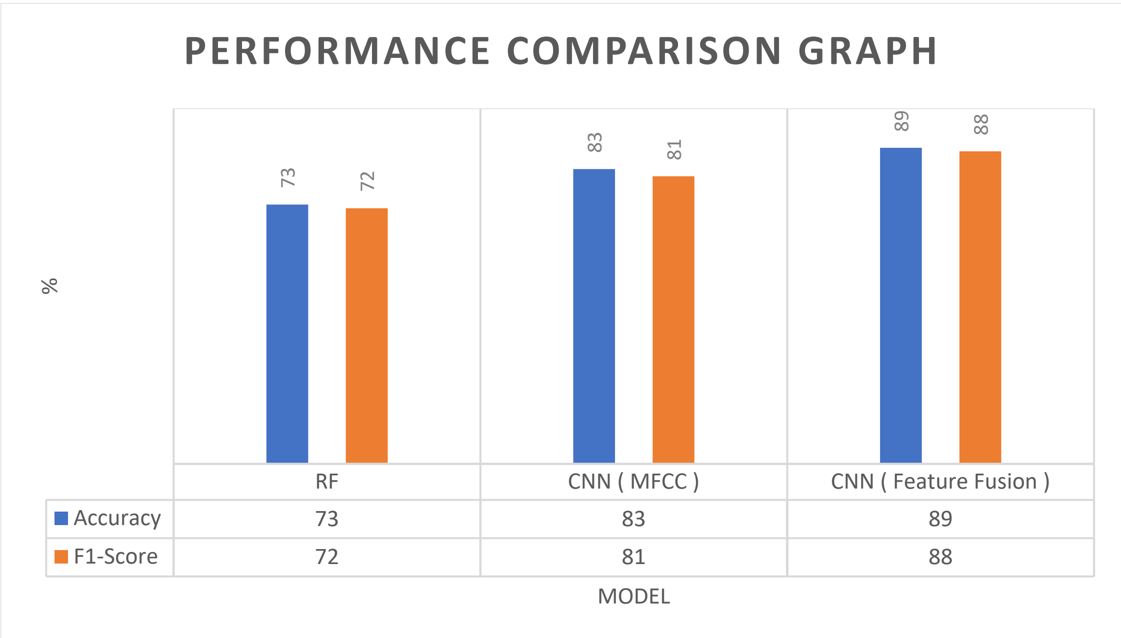

Figure 12. Performance Comparison Graph

Showed in Fig 12. the performance comparison graph are Random Forest (RF), CNN (MFCC), and CNN (Feature Fusion). With an F1-score of 72% and an accuracy of 73%, RF exhibits average competence but struggles to detect intricate patterns. Thanks to its capacity to adequately handle MFCC characteristics, CNN (MFCC) performs better with an accuracy of 83% and an F1-score of 81%. With the greatest accuracy (89%) and F1-score (88%), CNN (Feature Fusion) model performs better than both utilising many kinds of features at last. This reveals how strong and efficient feature fusion is in enhancing heart sound analysis categorisation performance.

VI. CONCLUSION

This work investigates how deep learning and machine learning models could be used to heart sound classification. It achieves this by comparing the performance of CNN (MFCC), Random Forest, and CNN (Feature Fusion) models. Although the Random Forest model was fast to run on a computer and simple to grasp, its only mediocre accuracy and F1-score indicates that it cannot manage intricate patterns in the heart sound data. The CNN (MFCC) model made really notable gains. Higher accuracy and improved generalisation followed from better recording of temporal and spectral data using MFCC characteristics. The most dependable and practical technique proved to be the CNN (feature fusion) model. Using many kinds of features—such as statistical, spectral, and MFCC—this model exceeded the others in accuracy (89%) and F1-score (88%). The feature fusion approach was rather beneficial in obtaining a complete image of the heart sound data, therefore enabling the model to operate well across all classes—including those with loud or non-well represented frequencies. With decreased training and validation losses and improved classification results for challenging classes like "Extrasystole" and "Noisy Normal," loss comparison and confusion matrix experiments revealed that CNN (Feature Fusion) functioned even better. Errors in certain groups, however, highlight the requirement of feature extraction even more and the fixing of class mismatches is necessary.

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