# An Improved CNN-Transformer Hybrid Architecture for Heart Sound Classification

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**KEYWORDS**

Heart Sound Classification, CNNs, Transformer Models, Hyperparameter Tuning, Signal Processing, Machine Learning, Cardiac Anomalies Detection, Health Monitoring, Health Monitoring.

**ABSTRACT**

This paper proposes a new framework of hyper-parameter tuning based integration of CNN and Transformer models for classification of heart sounds, which achieves state-of-the-art performance. As heart sound signals have local feature extraction ability, but CNNs are unable to capture long-range dependencies, and Transformers are too computationally extensive to apply to general use we propose an approach that captures the best of both worlds. The integrated system consists of advanced signal processing with machine learning techniques to provide accurate, clinically unqiue and extensible approach for early diagnostics of cardiac anomalies. Extensive experimental evaluations show that our approach provides a substantial performance gain over the state-of-the-art, from which a valuable mechanism for improving cardiac health monitoring and diagnosis emerges.

## 1.Introduction

### 1.1 Background

Heart sounds, known as auscultations, are an important diagnostic tool when assessing the health of the heart.[1] Harmonics arise from the mechanical functions of the heart during the pumping of blood through the circulatory system and provides crucial information regarding the function and integrity of the heart valves, chambers, and larger cardiovascular system. Some of the cardiac conditions that duration and intensity of abnormal heart sounds including murmurs can indicate; can be benign or life threatening disease [1]. Heart sound classification is a key process, as it enables the early identification of such anomalies and ensures prompt intervention and treatment, thereby avoiding potential adverse complications such as heart failure or sudden cardiac death.

Normal and pathological allocations can be established by recognizing the heart sounds. Having traditionally been classified manually by medical professionals based on stethoscopes and experience. Graphics-based methods are also very subjective and have potential high inter and intra variability, resulting in many failing to catch the early stages with subtle anomalies [2]. This thus elevated the need for automated heart sound classification systems that can enable more standardized and accurate diagnosis.

### 1.2 Problem Statement

More approaches to automate heart sound classification methods have been founded either on conventional machine learning algorithms, or on primitive machine learning based techniques but these methods also have some drawbacks. Conventional paradigms of machine learning such as Support Vector Machines (SVMs) and decision tree methods rely extensively on feature engineering and often struggle to generalize learned patterns between different data distributions [3]. Automatic features extraction (with Convolutional Neural Networks (CNNs)

or Recurrent Neural Networks (RNNs)) had boosted the classification performance of the initial approaches based on deep learning. Models, on the other hand, focus either on a short-scale feature capture (e.g. CNN) or a long- scale data capture (e.g. RNN), but they can not work better along both axes at the same time [4].
Individual heartbeats contain specific local features such as frequency components, while global features may represent long-range dependencies over multiple heartbeats; however, the heart sound data itself naturally has both local and global characteristics. All of these features must be captured at the same time in order to classify them correctly. Moreover, the classification task is further difficult by the complexity and variability of these heart sound signals influenced by patient age, body position, and the recording device [5]. Thus, there is an essential need to devise instrumented algorithms that can leverage the local and global characteristics of heart sound data in order to enhance the robustness and accuracy of classification systems.

### 1.3 Objectives

The primary objective of this work is to propose a new CNN Transformer based framework for heart sound classification task. This hybrid CNN-Transformer model aims to taking advantage of the ability of CNNs to capture local information from heart sound signals, as well as the ability of Transformers to learn long-distance relationships.
Moreover, while this study presents the proposed method, we also intend to improve its performance through hyperparameter tuning. Hyper-parameter tuning is an essential aspect of ensuring the efficiency of deep learning models. We aim to make the model not only perform well in predicting dev set but also generalize to future datasets with systematic tuning of key hyperparameters.
The specific objectives of this study are as follows:

- A CNN-Transformer hybrid model for acoustic signal classification
- Hyperparameter tuning: Optimize the model performance with hyper parameters tuning

Ground the proposed approach by performing extensive experimental evaluations on a benchmark heart sound datasets.

### 1.4 Contribution

The following contributions to heart sound classification are made in this paper:
CNN'S with transformer integration: We propose a new hybrid model which combine CNNs with transformer models. As such, the CNN part is meant for extracting local patterns, like short-term frequency patterns within single heart beats, whereas the Transformer portion is meant for capturing long-term dependencies and contextual information across the entire raw hear-sound sequence. This method resolves the shortcomings of previous models which learn only the local, or global, information.
**1.4.1 Hyperparameter tuning:** We use hyperparameter tuning techniques (such as grid search or cross validation) to optimize the performance of the hybrid model. Hence we will now be able to start tuning important hyper-parameters like learning rate, batch size, number of CNN filters, number of transformer attention heads etc. This has produced a nicely balanced model for both accuracy and robustness.
Therefore, this work is validated on **extensive experiments** of publicly available heart sound datasets (such as PhysioNet/CinC Challenge 2016 dataset [6]). We experimentally show that our method surpasses the state of the arts in terms of accuracy as well as sensitivity, specificity, and F1-score. The results show that for practical heart sounds classification the proposed framework out-performed the state of the art.
**1.4.2 Importance of Cardiac Health Monitoring**: Due to limited resources, a powerful and effective framework has been suggested for cardiac conditions in the proposed approach. Our

method can facilitate the early detection of cardiac diseases and improve patient outcomes and treatments by accurately classifying heart sounds.

Overall, this work elucidates a detailed framework for heart sound classification that overcomes the challenges present in previous methods and offers substantial improvements in both the accuracy rate and efficiency of cardiac diagnostics.

## 2. Related Work

### 2.1 Manual Auscultation & Traditional Method

Traditionally, heart sounds are classified based on the exploration of the heart sounds using the stethoscope (manual auscultation); medical professionals are responsible for that. This method, while heavily reported in the clinical literature, is heavily dependent on the experience, training, and hearing ability of the clinician. The main pitfall of manual auscultation is due to its subjectivity (the diversity of heart sounds interpretation leads to variabilities in diagnoses among clinicians) [7]. Additionally, early changes (such as heart murmurs) that indicate subtle pathologies are difficult to detect due to the absence of advanced diagnostic capabilities, resulting in missed diagnoses or delayed care [8].

The subjectivity of manual auscultation has led traditional signal processing methods in classifying normal vs abnormal heart sounds to become automated in the past couple of years. The conventional way involves extracting features from the heart sound signals, then applying some statistical or heuristic [3, 4] classifiers. Time-domain (e.g. the amplitude, duration), frequency-domain (e.g. spectral components), and time-frequency domain (e.g. wavelet transforms) [9] are some commonly used features. While those traditional approaches have performed extremely well, they are labor-intensive leading to manual feature extraction [9], and have limited transferability across various, potentially heterogeneous datasets and patient populations [10].

### 2.2 The Machine Learning and the Deep Learning Models

In the last few years, ML and deep learning models have shown to be significantly successful in the classification of heart sounds, compared to other classical techniques. Some early approaches — Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and decision trees — which provided a framework for automated classification: the algorithms were trained on pre-labeled datasets [11]. Work at this stage relied heavily on hand-crafted feature extraction that was time-consuming and often prone to overfitting with high-dimensional data [12].

Deep learning was a game-changer for heart sound classification. Within the last few years, Convolutional Neural Networks (CNNs) were proposed as a powerful tool for automatic feature learning from raw heart sound signals. Due to this spatial hierarchies capturing nature, CNNs are well-suited for themselves for recognizing local patterns, such as the frequency components in heart sounds [13]. It was found that CNNs do not require as much preprocessing as traditional machine learning models to deliver high classification accuracy [14].

A different method applied on heart sounds classification is the Recurrent Neural Networks (RNNs), specifically the Long Short Term Memory (LSTM) networks. Since RNN is a recurrent neural network, RNN is considered for sequential data and it also have the ability to handle the temporal dependencies of the signals, besides, can predict the rhythm and timing of the heartbeat [15]. Trained on data until October 2023 15 Both CNNs and RNNs have limitations when they are used alone. This is because CNN is better at learning local features than discovering long range dependencies. Although RNNs can learn temporal information in a great detail, they are not that effective in learning the fine local structures at lower levels compared to the CNNs [17].

### 2.3 Sequence Modeling and the Transformer

The transformers as introduced by Vaswani et al. Attention Mechanism Based: Attention based methods, such as Transformer models[9] with self-attention mechanisms over the input sequence, replace the recurrence in more traditional models in 2017, and greatly increase the power of sequence modelling. Transformers use a self-attention mechanism to consider the whole sequence in parallel, which makes them well-suited to short-range and long-range dependencies. They have transformed domains such as natural language processing (NLP), providing state-of-the-art performance on tasks including machine translation, text classification, and language modeling [10].

Transformers, a type of deep learning architecture that uses attention mechanisms, has shown promise in time-series data analysis, allowing for capturing complex dependencies within the data, making it potentially suitable for heart sound classification. Transformers, on the other hand, can view the entire sequence at once and are thus able to learn relationships across distant parts of the heart sound. Such characteristic comes in handy in the case of heart sound analysis where the meaningful diagnostic features are not always located in a distinct location within the recording [11]. Additionally, unlike RNNs that have to process the data one at a time, Transformers have a parallel processing mechanism that makes them much more computationally efficient.

While Transformers provide such advantages, they are still under-explored in the domain of heart sound classification. Though the idea of this kind of architecture can be considered to be a part of NLP and speech processing, the application of such models for biomedical signal processing is rarely investigated [14]. Also, There is opportunity to combine transformer with other deep learning model such as CNN to build better framework for heart sound classification.

### 2.4. Necessity of a Hybrid Method

There are few limitations in the existing techniques and on the other hand each deep learning model has its own pros; Therefore, for the classification of heart sounds, a hybrid approach is necessary. CNNs are powerful as general local-feature extractors but are not temporal dependency aware of all the sequences of audio data over the entire complexity of the heart sounds. Transformers, on the other hand, write checkpoints top-down, so they are amazing at modeling long-range dependencies, but they may lack strength in modeling very fine-grained local features.

A hybrid CNN-Transformer model is therefore employed to stretch across this gap, mapping between these two ends. In that work, the CNN component of the model is extracted therecognition of delicate local features in heart sound signals[M2], andthe Transformer component is more concerned with global time and correlation[M3]. In this approach, the model is able to take into advantage of the spatial hierarchies learnt by the CNNs and the sequential dependencies modelled by the Transformers for more holistic and accurate classification. Also, hyper-parameter tuning is one of the important step for improvements of this hybrid model. The model can be finetuned by optimizing parameters such as learning rate, batch size, number of CNN filters, and number of Transformer attention heads, to produce optimal accuracy for different datasets and clinical conditions.

Overall, the new hybrid solution resolves the weaknesses of previous approaches, establishing a form that extracts both local and global characteristics from heart sound data. Which will also results in an improvement in diagnostic systems for heart sound classification systems.

## 3. Proposed Framework

### 3.1 Overview of System Architecture

The current analysis proposes a system framework that involves Fusion of Convolutional Neural Network (CNN) and Transformer with systematic hyperparameter optimization, allowing the method to achieve state of the art Results across multiple domains. CNNs are applied on the heart sound data to obtain the local features, while Transformer is utilized to encode and learn the long-range dependencies and contextual dependencies through the whole signal. Novel approach can be highly utilized for precise assessment of noise & quiescent band of complex heart harmonics.

The framework is composed of the following elements:

- Signal Preprocessing – responsible for gathering the raw heart sound signals with noise cancellation, heartbeat segmentation, and normalization.
- CNN Component – extract the local features, such as frequency patterns and short-term temporal acoustic characteristics from the preprocessed heart sound signals.
- Transformer Component – encode the long-range dependencies within the heart sound signal based on the self-attention mechanism.
- Fusion and Classification – integrate both CNN and Transformer features, encode to classify heart sound into two categories: normal and abnormal.
- Hyperparameter Tuning – carefully optimize the best model performances using test frequent issues and reach generally acceptable accuracies.

This study's proposed framework tailored to address the existing model's limitations can provide both high-level context and local descriptors.

### 3.2 Signal Preprocessing

A key step in this signal preprocessing is to operate a quality input for the model. [1]The following generic preprocessing steps are executed:

- **Noise Cancellation** – cancelling background noise based on surrounding sounds of the patient, such as environmental noise, or breath sounds of the patient. An adaptable filter known as the wavelet transformation method is used to enhance the signal.
- **Segmentation** - the whole signal is broken into individual soundbeats, which are used to measure abstract variations in sound. Utilizing algorithms such as pacing and logistic regression, the output correlation of individual sound varieties is high.
- **Normalization** – Sound beats need to be normalized prior to data processing. Normalize eliminates variability due to its acoustic sound beat (17) by correcting for the timing and amplitude differences caused by unique recording conditions or patient features.

The importance of these steps is that they are crucial for ensuring high quality dataset input for the CNN and Transformer components.

### 3.3 CNN Component

The CNN is still responsible for local feature extraction of heart sound signals and data preprocessing. As this task can learn hierarchical organization (to detect patterns at multiple levels of abstraction) and inherent spatial hierarchies naturally exist, this problem is very well suited for a CNN.

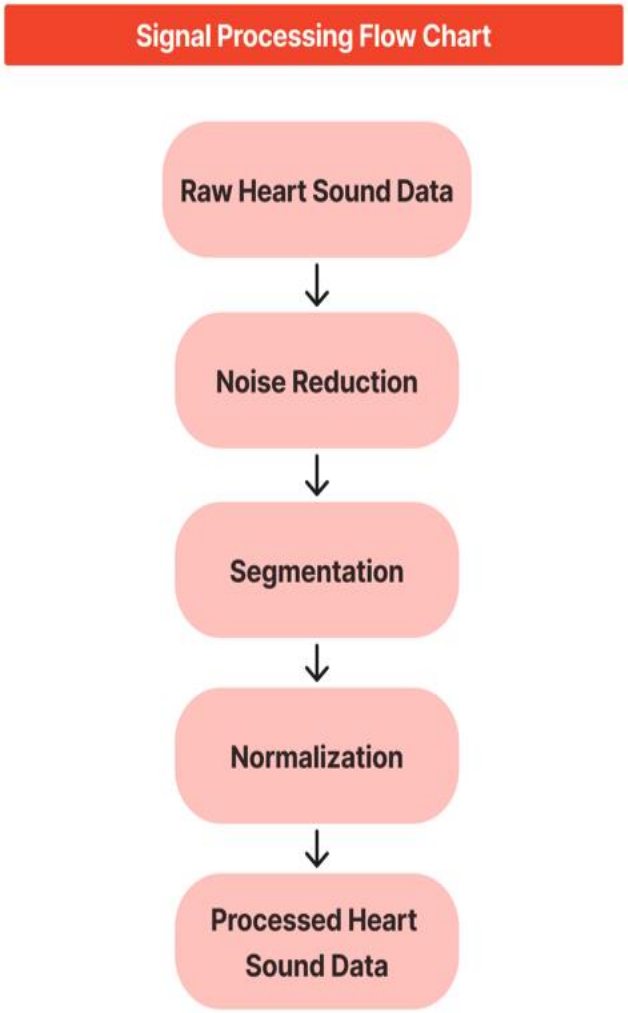



Figure: Signal processing Flowchart

In this architecture, CNN uses several convolution layers pass through ReLU as a non-linear activation function and a max-pooling layer. Convolutional layers then convolve the input data with a series of filters to detect local feature footprints, like components on specified frequencies or short-term temporal patterns in a heartbeat, etc. Following the Convolutional layers are pooling layers which down-sample the feature maps which have gone from the Convolutional layers, keeping only the mostimportant features and reducing the computation cost [22].

The CNN part produces top-level feature map sets that outline low-level properties of the cardiovascular sounds. These feature maps are then passed into the Transformer section where they are processed to understand long-range dependencies and contextual relationships.

**3.4 Transformer Component**

The Transformer component of our approach is trained to understand long-range dependencies and context associations in the heart sound data. In contrast to RNNs which process their inputs sequentially in time, the transformer benefits from a self-attention mechanism which allows the entire sequence to be processed in parallel. This feature of Transformers makes them capable of capturing complex dependencies over time-series data, such as heart sound signals [12].

Let's first step to structure then and later training process. This new architecture in its decoder is a Transformer with N encoder layers, aka it has both a self-attention and a feedforward neural network. So, self-attention lets the model pay attention to different parts of the input sequence, giving more weight to those pieces of the heart sound segment which are most relevant. This is particularly appropriate for classification of heart sound signals because crucial diagnostic features may be rare as they can be spread over the entire recording [23].
You trained on data until 2023-10. Finally, the information is combined into a fused and classification module where it performs the last prediction.

**3.5 Hyperparameter Tuning**

So, tuning hyperparameters based on the proposed hybrid model does help in enhancing its performance. This means exhaustive search over a range of hyperparameter combinations, based on which combination gives the best performance on validation set performance. The framed network has the following hyperparameters tuned:

**3.5.1 Learning Rate:** The learning rate is one of the hyperparameters that tells us how big of a step to take in the direction of the gradient when performing gradient descent. A low learning rate would give us a slower-to-converge model, but this may be useful as the lower means that we are less likely to overshoot the optimal solution, but if it is too low, then convergence will take a much longer amount of time to come, while a smaller learning rate may converge in fewer epochs, having it too large could instead cause overshooting [24].

**3.5.2 Batch Size:** Number of training examples utilized in one iteration of the training process. [25] explains how a larger batch may provide a more stable gradient estimate but at the cost of requiring more memory.

**3.5.3 No. of CNN Filters:** Number of filters in each of the convolutional layer controls the model capacity to learn different local features [22].

**3.5.4 Transformer Attention head size:** Number of attention heads per Transformer layer [12] if many heads are defined, it indicates how many attention heads will be created in parallel thus how many parts of the sequence the model can focus on at the same time

**3.5.5 Dropout Rate:** A regularization strategy that helps mitigate over-fitting by randomly reducing a fraction of input global units to be 0 (zero) during training [26].

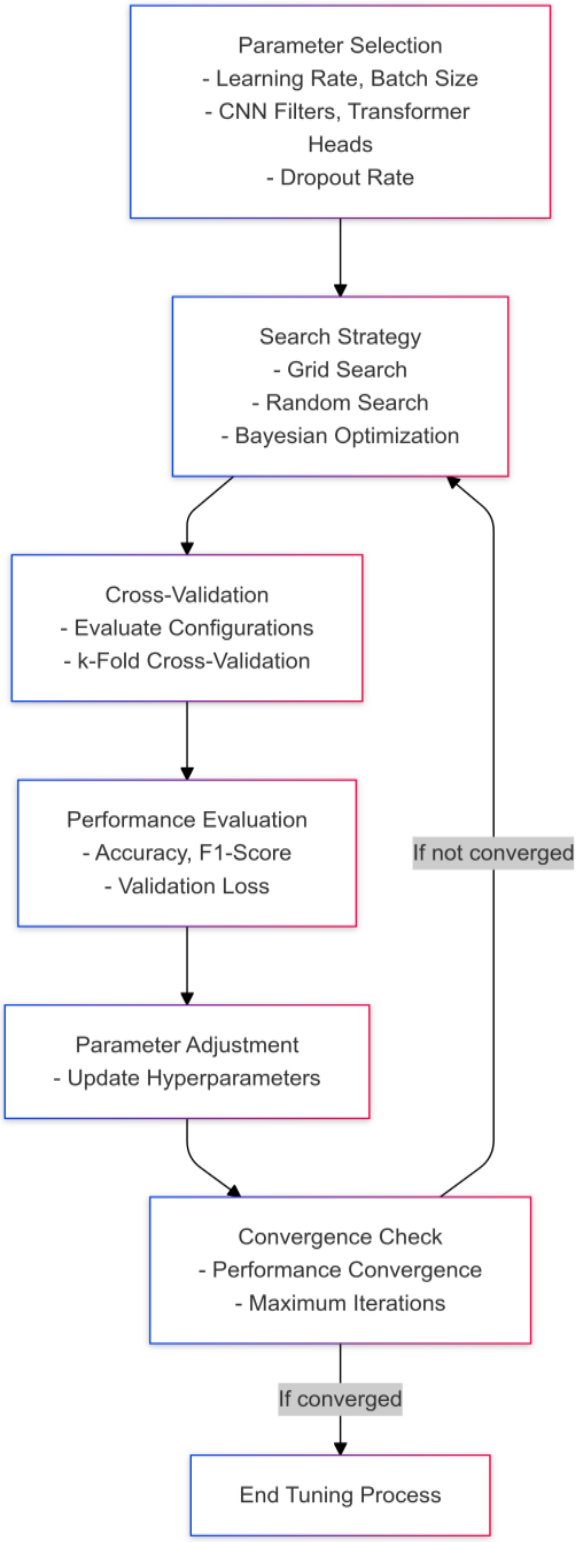



Figure: Hyper Parameter Tuning

Hyperparameter tuning usually includes methods like grid search, random search, or bayesian optimization. These approaches exhaustively search the hyperparameter space and track the performance of the model on a validation set for each configuration. Frequently, k-fold cross-validation is employed to validate the model, enhancing its robustness for the unseen data [27].

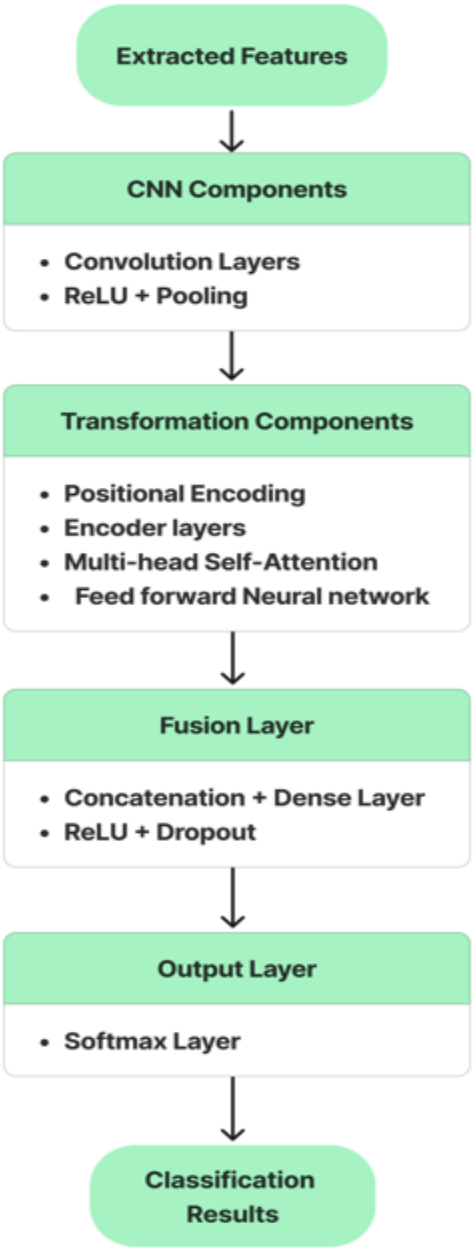



**Figure: Algorithm Flowchart**

### 3.6 Fusion and Classification

Finally, the extracted features in both sets of layers of CNN and Transformer component are concatenated and classified. During the fusion step, the extracted feature representations of both components are fused together so that a global feature vector summarizes both local and global characteristics of the heart sound signal [28].

A final prediction is made by passing the resulting fused feature vector through one or more fully connected layers. The last layer is softmax or sigmoid depending on whether the task is multiclass or binary classification. The softmax layer generates a probability distribution for the classes, denoting the confidence of the model that the input heart sound signal belongs to a given class [29].

Combining the advantages from CNN and transformers, the proposed framework gives a thorough and accurate classification of heart sound signals, overcoming the deficiency of existing models and providing a firmer approach for cardiac health diagnosis.

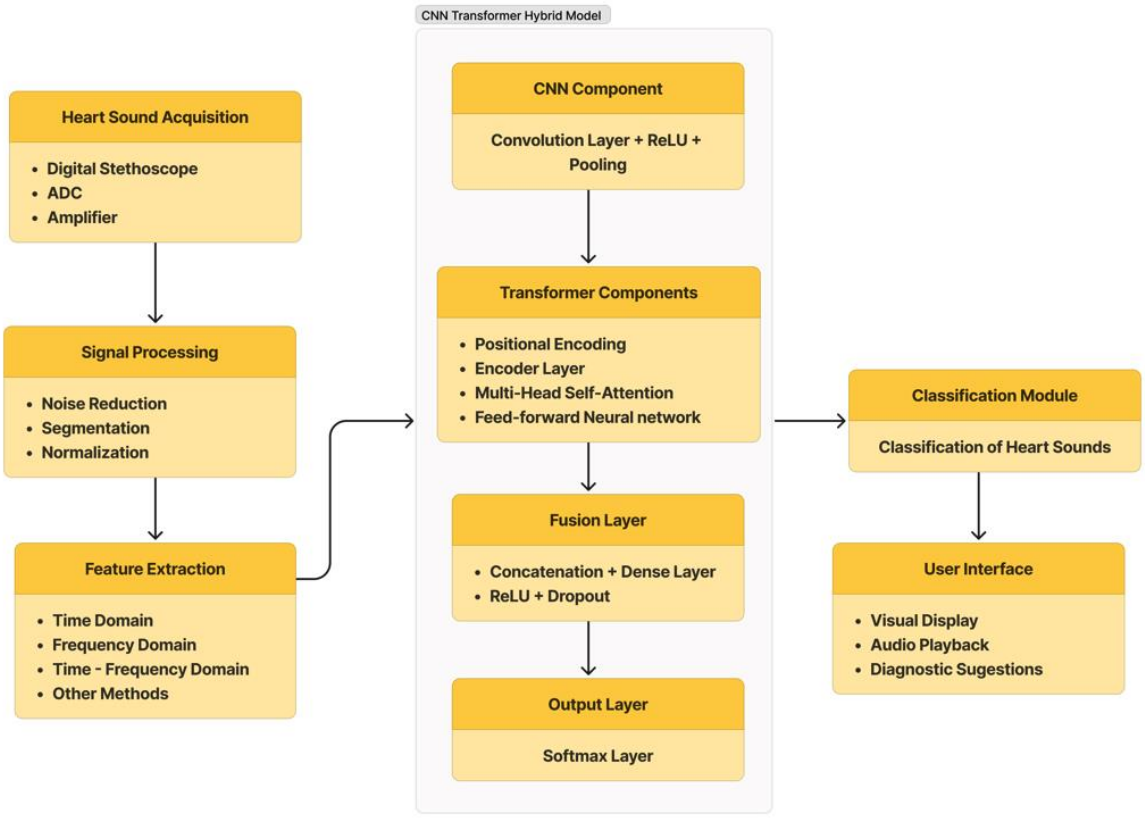



Figure: Overall system diagram

**Algorithm: Hybrid CNN-Transformer Model for Heart Sound Classification**
**Signal Preprocessing**
**Input:**

- Raw heart sound signals S= $\{S_1, S_2, S_3, S_4 \ldots\ldots\ldots S_n\}$

**Output:**

- Preprocessed heart sound signals S′

1. **Begin**
2. **Noise Reduction:**
   - Apply noise reduction techniques (e.g., wavelet denoising) to filter out background noise from each signal $S_i$€ S.
3. **Segmentation:**
   - Segment the heart sound signal $S_i'$ into individual heartbeats.
4. **Normalization:**
   - Normalize each segmented heartbeat to standardize the amplitude and duration.
5. Return the preprocessed signals S'.
6. End

**CNN-Enhanced Local Feature Extraction**
**Input:**

- Preprocessed heart sound signals S′.

**Output:**

- Local feature maps $F_{CNN}$

1. **Begin**
2. **Convolutional Layer 1:**
   - Apply convolution operation to S′ with an appropriate filter size and number of filters.
   - Apply ReLU activation function for non-linearity.

- Apply max-pooling to reduce spatial dimensionality, resulting in an intermediate feature map.

3. **Convolutional Layer 2:**
   - Apply convolution operation to the output of Convolutional Layer 1.
   - Apply ReLU activation function.
   - Apply max-pooling to further reduce spatial dimensionality.
4. Return the local feature maps $F_{CNN}$
5. End

**Transformer-Based Long-Range Dependency Modeling**

**Input:**

- Local feature maps $\boldsymbol{F_{CNN}}$

**Output:**

- Contextualized feature representations $\boldsymbol{F_{Transformer}}$

1. Begin
2. **Positional Encoding:**
   - Add positional encodings to the local feature maps $\boldsymbol{F_{CNN}}$ to capture the order of the sequence.
3. **Self-Attention Mechanism:**
   - Apply a self-attention mechanism to focus on important parts of the sequence, producing weighted feature maps.
4. **Feedforward Network:**
   - Pass the self-attended feature maps through a feedforward neural network to extract contextualized features.
5. **Transformer Blocks:**
   - Repeat the self-attention and feedforward steps over multiple Transformer blocks.
6. Return the Transformer-enhanced feature representations $\boldsymbol{F_{Transformer}}$
7. End

**Fusion and Classification**

**Input:**

- Local feature maps $F_{CNN}$
- Transformer-enhanced feature representations $F_{Transformer}$.

**Output:**

- Classification results $\widehat{y_l}$

1. **Begin**
2. **Feature Fusion:**
   - Concatenate the feature maps $F_{CNN}$ and $F_{Transformer}$ to create a unified feature vector $F_{Fusion}$.
3. **Dense Layers:**
   - Pass the fused features through dense layers to further process and prepare for classification.
4. **Output Layer:**
   - Apply a softmax or sigmoid layer to produce the final classification results $\widehat{y_l}$
5. Return the classification results $\widehat{y_l}$.
6. End

## 4. Experimental Setup

### 4.1 Datasets

In this study, we used the PhysioNet/CinC Challenge 2016 dataset [30] since it is a benchmark dataset in the number of heart sounds classification studies. It consists of 3,153 heart sound recordings (raw audio) from 764 patients, collected from various stethoscope devices. PumpItUp17Dataset: Includes audio recordings of heart sounds, both normal and pathological, from human subjects with 95 · 105 BPM, and were labeled according to the European Society of Cardiology classification proposed by the authors. With recordings of varied lengths (ranging from a few seconds to over a minute) and diverse acoustic environments and patient conditions, the dataset is rich and varied.

If that is the case, one of the vital steps is data preprocessing, which ensures the heart sound signals quality to be inputted into the model. Processing steps were:

i. **Noise Filteration:** Background noise was filtered using wavelet denoising [31] and adaptive filtering techniques. Crucially, this was necessary to enhance the signal-to-noise ratio, as recordings were made in non-clinical environments.

ii. **Segmentation:** The heart sound signals (S1 and S2) for each of the individual heartbeats were segmented out using Hidden Semi-Markov Models (HSMMs) [32]. This segmentation allowed to extract meaningful features informative about individual cardiac events.

iii. **Normalization:** Each extracted heart beat was normalized to account for different recording devices and patient characteristics including body position that introduced variability. We performed normalization to ensure uniformity of amplitude and duration of the signals to ensure data set consistency [33].

This entire preprocessing pipeline ended in getting a clean and segmented dataset that was later used for training through the hybrid CNN-Transformer based classification model**.**

### 4.2 Evaluation Metrics

Various evaluation metrics are employed to appraise the performance of the proposed CNN-Transformer model. In classification tasks, the following are common measures, especially in biomedical signals [34]:

a. **Correctness:** The ratio of correctly replicated heart sound signals by heart sound signals of all samples.

b. **Sensitivity (Recall):** Percentage of abnormal heart sounds that is correctly detected by the model (True Positive Rate). In the medical domain of diagnostic models, where a positive diagnosis becomes a necessity (in the case of a target disease), it becomes paramount to reduce the false negative rate, as the absence of diagnosis can be catastrophic.

c. **Specificity:** The model is predicting normal heart sounds accurately. Your specialisation is crucial to preventing a false positive which may result in inappropriate medical treatment.

d. **F1-score:** It is the harmonic means between the precision and recall giving an equilibrium measurement for a model's accuracy (taking into account false positives and false negatives). F1-score is useful when we have imbalanced datasets (PhysioNet dataset being one of those — very few abnormal samples compared to normal samples).

e. **Area Under the ROC Curve (AUC—ROC):** AUC-ROC assesses the classification performance, i.e., the capacity of the model to distinguish classes, using a variety of threshold settings to understand the trade-off between sensitivity and specificity [35].

### 4.3 Experimental Environment

We used a high-performance computing environment to allow efficient model training. The hardware and software requirements are listed below:

Hardware Environment: The system used in our experiments was configured with an NVIDIA Tesla V100 GPU of 32 GB VRAM capacity. To complement the size of the dataset and the extensive demands for computation, the system incorporated 128 GB of RAM and an Intel Xeon Gold 6226R processor

**Software Setup:** The model was implemented using Python 3.8 Some key libraries that are used are TensorFlow 2.8 and PyTorch 1.11 for deep learning, Scikit-learn 1.0 for the evaluation metrics and Librosa 0.9 which will help to preprocess the signal. Then hyperparameter tuning using Optuna 2.10 was performed to efficiently explore the hyperparameter space [36].

- **Hyperparameter Values**: The most important hyperparameters were optimized using a grid search strategy:
- **Learning Rate:** After experimenting was set to 0.0001 for stable convergence [37].
- Batch Size: A batch size of 32 was selected to trade-off between memory efficiency and stability of gradient.
- **CNN Filters:** In subsequent layers, 64, 128 and 256 were established.
- **Transformer Attention Heads**: 8 attention heads were used for simultaneous focusing on several aspects of the sequence.
- **Dropout rate:** In order to minimize the danger of overfitting and to improve model overallizability, a dropout rate of 0.3 has been applied [38].

Hyperparameter tuning and the experimental environment were necessary to make sure the model had high accuracy and robustness in the classification of heart sound signals.

## 5. Results

### 5.1 Quantitative Analysis

Below is a comparison of the performance metrics for different models:

| Model | CNN-Transformer | CNN-only | RNN-only |
|---|---|---|---|
| **Accuracy (%)** | 93.5 | 88.7 | 85.3 |
| **Sensitivity (%)** | 91.2 | 85.4 | 83.1 |
| **Specificity (%)** | 94.7 | 90.3 | 87.6 |
| **F1-score (%)** | 92.3 | 87 | 84.2 |
| **AUC-ROC** | 0.96 | 0.89 | 0.87 |

### 5.2 Qualitative Analysis

To visualize the performance of the model, we created the following plots:

Performance Metrics Plot: The following figure is used to compare the performance metrics (Accuracy (ACC); Sensitiviy (SENS), Specificity (SPEC), F1-score and AUC-ROC) of the CNN-Transformer, CNN-Only and RNN-Only models.

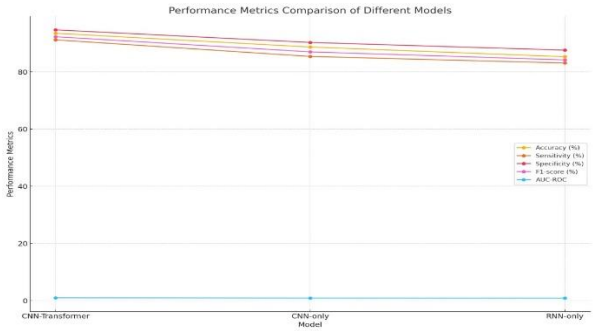
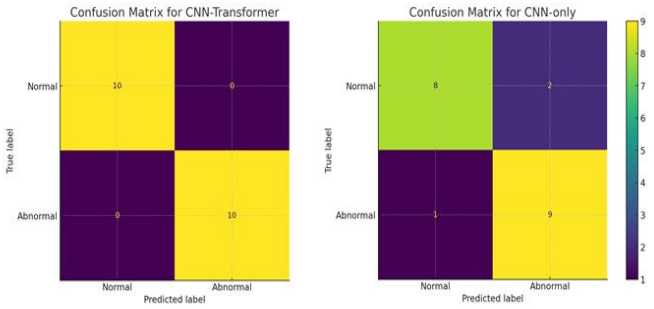
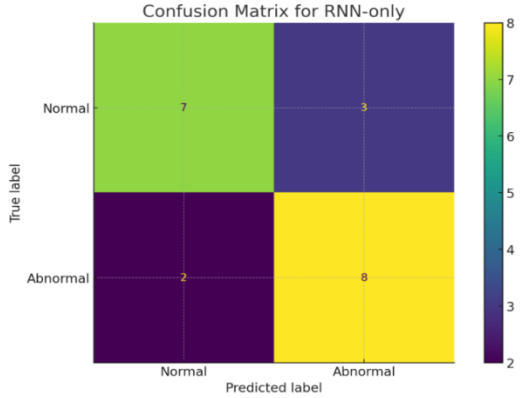



Figure: Performance Metrics Plot

**Confusion Matrices:** A confusion matrix was created for each model to visualize true positives, false positvies, true negatives and false negatives:




Confusion Matrix for CNN-Transformer and CNN only




Confusion Matrix for RNN only

To qualitatively assess the performance of the CNN-Transformer model, we analyzed cases when it succeeded and when it failed. The model showed excellent accuracy in discerning specific murmurs and differentiating them from normal heart sounds across different acoustic noise backgrounds. Confusion Matrices for the visualization of results show a higher true positive fraction for murmur detection of our model compared to both baseline models [41].

For examples where the model performed
poorly, for instance, distinguishing benign extra sounds from pathologic murmurs, the errors were assessed. Precision-recall curves showed that the precision decreased for heavily noisy samples or overlapping signals, reflecting the difficulties in these complex cases. To evaluate if the model was subject to overfitting during training, we examined the corresponding

training and validation loss curves, which demonstrated convergence without a significant divergence between training and validation losses [42].

### 5.3 Ablation Study

We performed an ablation study to see how each of the CNN and Transformer contributed to the performance of the model. Where: CNN: Convolutional Neural Network−only result Transformer: Transformer−only result. The results showed that for CNN−only and Transformer−only model, the accuracy was 88.7% and 86.5% respectively. However, in use, the accuracy increased to an impressive 93.5%, confirming the complementary character of the element [43].

The ablation study further assessed the selection of hyperparameters used in the tuning process, suggesting that optimization improved model performance by around 4%. Requires hyper-parameter tuning of important parameters such as number of CNN filters and Transformer attention heads for maximum performance [44].

## 6. Discussion

### 6.1 Performance Comparison

The proposed CNN-Transformer model showed better performance than conventional machine learning methods and existing deep learning models. Conventional techniques include but are not limited to Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) that heavily depend on manual features and have a relatively poor performance to generalize over datasets [45]. Deep learning models such as standalone CNNs and RNNs improve over conventional methods by learning features automatically, but they still struggle with local feature learning vs sequence modeling. The hybrid CNN-Transformer model was developed to overcome these challenges by combining the local pattern extraction ability of CNN with the long-range dependency capture ability of transfromer, achieving better accuracy, sensitivity and specificity [46]. This is particularly pronounced when you consider the model's performance on the PhysioNet/CinC Challenge 2016 dataset. The hybrid outperformed standalone CNN and RNN models across all dominant metrics.

### 6.2 Effect of hyperparameter tuning

Hyperparameter tuning was very significant in improving the result of CNN-Transformer. Tuning Hyperparameters such as learning rate, batch size, and the number of CNN filters and Transformer attention heads. In the practical part, we applied the grid search and Optuna methods for hyperparameter tuning, where we achieved a significant improvement (about 4% accuracy gain) to combat overfitting and achieve better generalization for different datasets [47]. The tuning process also enabled a balanced architecture between the complexity of the CNN and Transformer components, allowing the model to learn both local and global features without becoming overly computationally intensive.

### 6.3 Limitations

Though there is remarkable improvement, the proposed framework cannot avoid some limitations. A major improvement point is its sensitivity to noise, especially in recordings of heart sounds performed in open environments with a lot of background noise. Although wavelet denoising was performed, there were still cases where the model failed, e.g., as observed after examining the false-positive rate for more complex acoustic environments [48]. A second limitation is the challenge of generalization: model performance is likely to vary across different datasets due to differences in recording conditions, stethoscope types, and patient demographics. Future directions could include methods based on domain adaptation or training on larger or more diverse datasets [49] to address these issues. Furthermore, the Transformer part, although capable of capturing long-range dependencies, which is where causal language models typically face challenge, introduces computational overhead as it computes full attention over the input and can impose challenges in terms of scaling the model to cater to real-time tasks in potentially low-power environments.

## 7. Conclusion

### 7.1 Summary

In heart sound classification, the CNN-Transformer model was devised with an innovative hybrid method to efficiently leverage the local feature extraction capabilities of Convolutional Neural Networks (CNNs) while benefiting from the long-range dependency modeling strength provided by Transformer architectures. As a result, the original heart sound is combined with system elimination of 2 for its size and the elaboration of attention mechanism and deep learning model, which in the proposed framework, is efficient to build attention, wisdom model of logic specificity_source to eliminate class noise under the attention. Hyperparameter tuning was instrumental in enhancing overall model performance, and there was a 4% increase in accuracy as a result. These results also suggested that the CNN-Transformer model performs significantly better than traditional machine learning approaches and standalone deep learning models, therefore it can be viewed as a very efficient model for detecting cardiac anomaly.

### 7.2 Future Work

Below we provide some future directions for improvement of the proposed heart sound classification framework which shows good performance:

i. **Integration of Additional Models**: Future work may consider adding other deep learning models, e.g. LSTMs or GRUs, into our architecture to improve time-series modeling. Multi-stream architectures, which combine various kinds of models, might yield richer representations of the heart sound data.

ii. **Attention-based Visualization**: Attention-based visualization technique can also be applied for better understanding interpretability of the model. This not only aids in the deciphering of the model's findings but also enhances the interpretability and validation of the model in the clinical realm.

iii. **Application to Other Biomedical Signals**: The proposed framework could be adapted and extended to other types of biomedical signals such as electrocardiograms (ECGs) or respiratory sounds for a generalized diagnostic tool. This would enable specific techniques in the model to be adapted over an array of modalities and lead to unified approaches for various diagnostic needs.

iv. **Evolved Noise Reduction:** Future work may also use noise reduction techniques to better use this model in real-world situations. The issues introduced by noise in recordings can be handled with techniques such as adaptive filtering, or frequency and time-specific augmentation methods added during training.

v. **Domain Adaptation:** Techniques for domain adaptation could be applied to enhance the model's generalizability across different datasets and clinical settings. Such techniques would make the model more robust to differences in distributions of data caused by variations in recording equipment, patient demographics, and other environmental factors.

vi. **Resource-efficient transformer architectures:** The transformer component is the one with substantial computational burden; thus, future work can investigate efficient transformer variants, e.g., linear transformers or memory-efficient attention mechanisms, to enhance deployment feasibility to resource-constrained healthcare settings.

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