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Heartbeat Sound Classification Using Deep Learning Techniques Over Raspberry Pi System

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Abstract: - This article focuses on the development of a heart beat sound classification system utilizing sound signals through the combined application of Convolutional Neural Networks (CNN) techniques over Raspberry Pi System. The proposed methodology involves the acquisition of heart sounds, preprocessing through signal analysis using CNN model accurate classification. By utilizing the stated algorithms, the aim is to determine task of heart rate classification.The core system leverages CNN model to effectively classify heart beat sounds. A diverse dataset comprising a range of heart conditions and rates is used to train and fine-tune both deep learning architectures. This approach allows for the extraction of intricate features from the audio data, enabling improved classification accuracy.The proposed system classifies heart beat sounds into categories such as normal, murmur, extra heart sound, extrasystole, and artifact. Through extensive training and validation, CNN model will learn to recognize distinctive patterns in the audio signals, facilitating precise classification of different heart beat sounds. Upon evaluation, the performance of CNN algorithm will be compared to determine the results in heart sound classification. The whole analysis process is carried on a Raspberry Pi machine, which is very cost-effective and portable device. The Raspberry Pi serves as an accessible platform for real-time heartbeat sound classification, making advanced cardiac monitoring technology more widely available. This comparative analysis will contribute valuable insights into the effectiveness of each approach in this specific application.

Keywords: Heartbeat sound classification, Convolutional Neural Networks (CNN), Raspberry Pi, Signal preprocessing, Heart conditions detection, Deep learning architecture, Cardiac monitoring system.

1.INTRODUCTION

The heartbeat, a fundamental physiological phenomenon of the human body, manifests as distinct sounds reflecting heart function. Influenced by age and lifestyle, these sounds are categorized as normal, extrasystole, murmur, extra heart sound, and artifact during the cardiac cycle, including the characteristic “lub-dub” associated with heart valve closure. These acoustic patterns contain valuable information about the heart’s performance. The extraction of detailed characteristics from audio files of heartbeats may be accomplished via the use of deep learning methods, like Convolutional Neural Network (CNN) [1,2]. The model will train on a diverse dataset encompassing various heart rates, capturing the variability in normal and abnormal cardiac conditions.

Moreover, this article includes the deployment of the developed model on a Raspberry Pi, a cost-effective and portable device. The Raspberry Pi serves as an accessible platform for real-time heartbeat sound classification, making advanced cardiac monitoring technology more widely available.The subsequent sections of this project will delve into methodology employed, the construction of the dataset, details of the deep learning model architecture and the outcomes of the classification process[3,4].By accurately classifying heartbeat sounds, this project aims to enhance the capabilities of health monitoring systems,

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offering a valuable tool for early identification of potential cardiac issues.

I. HEART BEAT CATEGORIES

- **NORMAL:** Normal heart beat has two main sounds “lub-dub”. It has a clear pattern of “lub-dub,lub-dub” and its rate is 60-100bpm.
- **MURMUR:** An irregular sound that may be detected throughout the cardiac cycle is known as a heart murmur.Interrupting the typical "lub" as well as "dub" heart sounds, it sounds like whooshing, blowing, or rasping. While most murmurs are harmless, some may signal underlying cardiac disease due to the turbulence they cause in the heart or blood arteries.

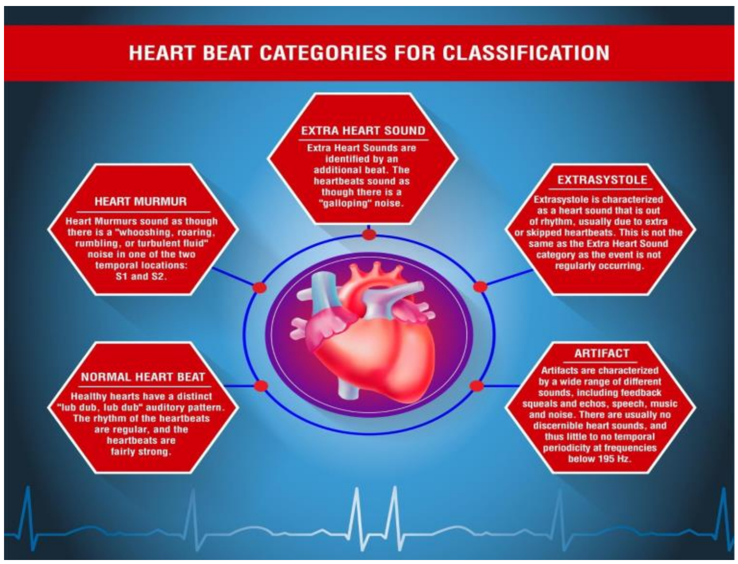

Figure 1.1: Heart beat categories

- **EXTRA HEART SOUNDS:** It involves additional beat that is more oftenly extra “lub - dub” , thatcreate a sounds like “galloping” noise like sound comes when horse moves or run faster.
- S3: This sound occurs immediately after S2 and is associated with rapid ventricular filling during theearly diastole.
- S4: This sound occurs just before S1 and is associated with atrial contraction against a stiff ventricle.It's also described as a low-pitched "gallop" sound and is often indicative of decreased ventricularcompliance, such as in hypertensive heart disease or aortic stenosis
- **EXTRA SYSTOLE:** This occurs when heart’s chambers contract earlier than they should, thisresults in extra beat causing a pause before the next normal heartbeat, it feels like skipped beat .Thepattern is like “lub-dub dub, lub-dub dub”.
- **ARTIFACT:** An artifact refers to unwanted signals or noise that can affect the accuracy of recordings, such as echoes or external interference. In the context of heart sounds, artifacts can distort recordings, making it

difficult to discern true heart sounds. They typically lack recognizable patterns and may have frequencies lower than 195Hz.The scope of this article involves collecting a diverse range of audio recordings capturing different heart rates, encompassing both normal and abnormal sounds. The purpose of this paper is to extract detailed characteristics from these recordings in order to identify a variety of heartbeat patterns [5-7]. This will be accomplished by using sophisticated deep learning methods such as convolutional neural networks (CNNs).The subsequent step entails developing and training both CNN model on the compiled dataset. The focus is on accurately classifying heart sounds into distinct categories such as normal, murmur, extra heartbeat, artifact, and extra-systole. Rigorous evaluation of the trained models follows, assessing their accuracy in correctly identifying different types of heartbeat sounds[8,9].Detecting heart rate accurately presents several challenges:

- **Individual Variations**: Baseline heart rates vary due to factors like age, fitness, and healthconditions, requiring algorithms to accommodate diverse populations.
- **Environmental Noise**: Noise from movement and external sources can distort heart ratemeasurements, necessitating robust filtering algorithms.
- **Physiological Changes**: Heart rate fluctuates during activities like exercise and sleep, requiring algorithms to adapt to dynamic changes.
- **Reliability During Activities**: Ensuring accurate measurements during movement is crucial,requiring devices and algorithms to mitigate motion artifacts.
- **Population-specific Challenges:** Certain conditions like arrhythmias pose challenges, requiring algorithms to differentiate between normal and abnormal rhythms.

Overcoming these challenges requires innovative approaches in signal processing and algorithm development to ensure accurate and reliable heart rate monitoring across diverse conditions.

2.OBJECTIVES

The objectives are centered on advancing the understanding and classification of heartbeat sounds using both Convolutional Neural Networks (CNNs). It begins with compiling a diverse and high-quality dataset that comprehensively representsvarious heart conditions, rates, and patterns[10-12].A pivotal objective is the development of robust CNN model, with the aim of extracting intricate features from heartbeat audio recordings for effective classification.

Through rigorous training and validation, the project aims to optimize the performance CNN model, particularly in accurately distinguishing between normal and abnormal heartbeat patterns. The project concludes with a comprehensive analysis, evaluating the classification performance of both models and assessing their potential impact on health monitoring system on the Raspberry Pi system..

3.LITERATURE SURVEY

Several studies highlight the use of deep learning models for automated ECG and heartbeat classification, significantly improving the detection of cardiac abnormalities[13-15]. Li Xiaolin et al. and Mayank Chourasia et al. both present 1D convolutional neural networks (CNNs) that classify ECG heartbeats into five categories with high accuracy. Xiaolin's model achieves 98.12% accuracy, ideal for wearable ECG devices, while Chourasia's system is designed to reduce the workload in cardiac clinics by automating feature extraction and classification.

Other research focuses on enhancing model adaptability and performance[16-19]. Mohammad Kachuee et al. propose a CNN with residual connections that leverages large datasets and transfers learned features between tasks. This method is particularly useful for tasks with limited data, enabling better arrhythmia detection and improving myocardial infarction (MI) prediction. Similarly, Janne Takalo-Mattila et al. introduce an inter-patient classification system, which shows that using patient-specific data enhances classification accuracy, especially when tested on large databases.

Additionally, deep learning is being applied beyond ECG to heartbeat sound classification[20-22]. Ali Raza et al. use a recurrent neural networks (RNN) with LSTM layers to classify heartbeat sounds into categories like Normal, Murmur, and Extra-systole. Their system achieves an accuracy of 80.80%, proving efficient for detecting abnormalities from heart sound signals and aiding in diagnosis[24]. These studies collectively demonstrate the potential of deep learning to transform cardiac diagnosis by automating and improving accuracy in ECG and heartbeat analysis[23,25].

4. PROPOSED SYSTEM

`The proposed system for heart beat sound classification utilizing deep learning employs a Convolutional Neural Networks (CNNs). Spectrograms and Mel-frequency cepstral coefficients (MFCCs) are examples of features that may be retrieved from cardiac sound signals and used as inputs to the network for the purposes of training and classification [26,27]. Using the ability of convolutional neural networks (CNNs) to detect complex patterns and changes that are built into heart sound data, a model is trained to differentiate between normal and pathological heart sounds [28,29].Preprocessing steps, data augmentation techniques, and model fine-tuning remain crucial aspects of system development, ensuring robust performance and generalization across diverse datasets and conditions, the system aims to enhance the classification accuracy and effectiveness of heart beat sound analysis, contributing to improved healthcare diagnostics and monitoring[30].

I.SYSTEM DESIGN

Designing a system for heart beat sound classification using deep learning involves several sequential steps and considerations. Initially, a dataset comprising heart beat sound recordings with appropriate labels indicating different heart conditions is collected. Then we augment the original dataset to obtain large dataset. Subsequently, the raw audio data undergoes preprocessing, which includes noise reduction, resampling, normalization, and possibly feature extraction techniques such as MFCCs or spectrograms to enhance model performance.

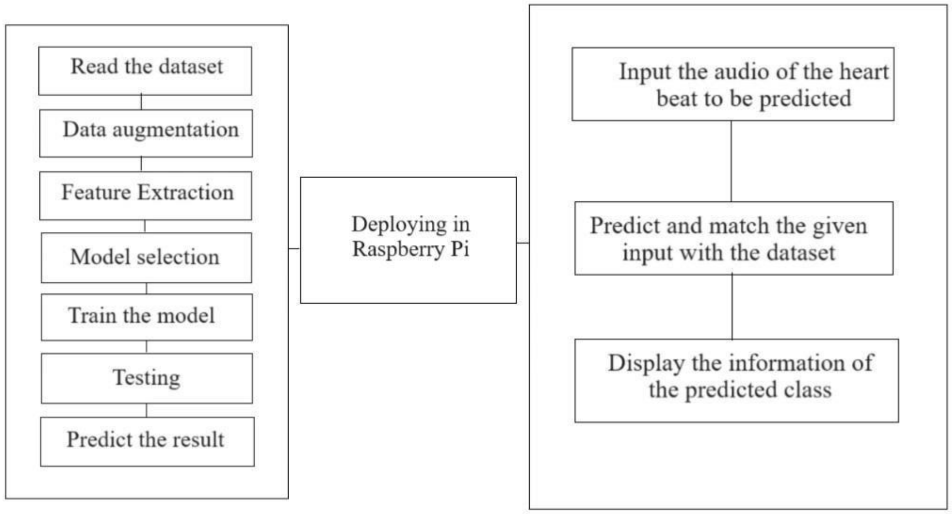

Figure 1. System Architecture

Following data preparation, an appropriate deep learningarchitecture is selected, which encompass CNNs. The chosen model is then trained usingthe preprocessed data. Subsequently, the trained model's performance is evaluated using a separate testset, employing metrics like accuracy. Post-evaluation, the model is deployed into real-world applications, integrated into software systems where it can receive input heart beat sound recordings and provide corresponding classifications. Finally to ensure accessibility and efficiency, the project is adapted for deployment on Raspberry Pi, considering hardware limitations and optimizing the model for inference on this platform.

II.CNN ARCHITECTURE

Constructing a heart beat sound classification system with deep learning involves a comprehensiveprocess to ensure accurate and reliable identification of normal and abnormal heart sounds.Firstly, obtaining a high-quality dataset is paramount. This dataset should comprise a diverse range of heart sound recordings, meticulously labeled to differentiate between normal heartbeats andthose with abnormalities.

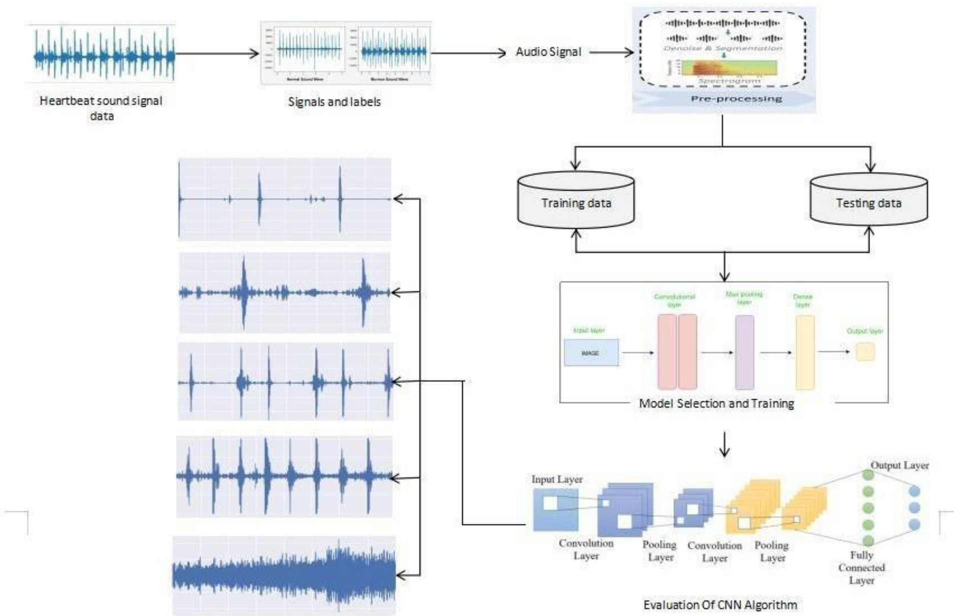

Figure 2. Architecture of the proposed system using CNN

These recordings could come from various sources such as healthcare institutions, research studies, or publicly available databases.Once the dataset is acquired, preprocessing the audio data is essential. This step involves converting the raw audio signals into a format suitable for deep learning models, such as spectrograms or Mel-frequency cepstral coefficients (MFCCs). Additionally, preprocessing techniques like normalization, standardization, and data augmentation are applied to enhance the quality and diversity of the dataset.

Next, designing an effective model architecture is critical. A Convolutional Neural Network (CNN) is commonly used for heart sound classification due to its ability to extract spatial hierarchies of features from input data. The input layer is populated with spectrogram or MFCC images, allowing the model to learn discriminative features for accurate classification.During the training phase, the model learns to classify heart sounds by adjusting its parameters to minimize classification error. This process involves feeding the preprocessed data intothe model, optimizing it using appropriate algorithms and evaluating its performance on a validation dataset. Hyperparameter tuning may be performed to optimize the model's architecture and improve its performance metrics.Rigorous evaluation ensures that the model can reliably classify heart sounds, particularly in real-world scenarios where it encounters unseen data.Finally, the validated model can be deployed for practical applications, such as integrating it into healthcare systems or mobile applications for remote patient monitoring. Continuous monitoring and refinement of the model are essential to ensure its effectiveness and reliability in clinical settings, thereby improving the diagnosis and the management of the cardiovascular conditions.

A.UNDERSTANDING AUDIO DATA

Audio data, representing sound waves, is characterized by its temporal nature, capturing changes in air pressure over time. The most common representation of audio data is the waveform, a plot of amplitude against time, illustrating the intensity and frequency components of the sound signal.

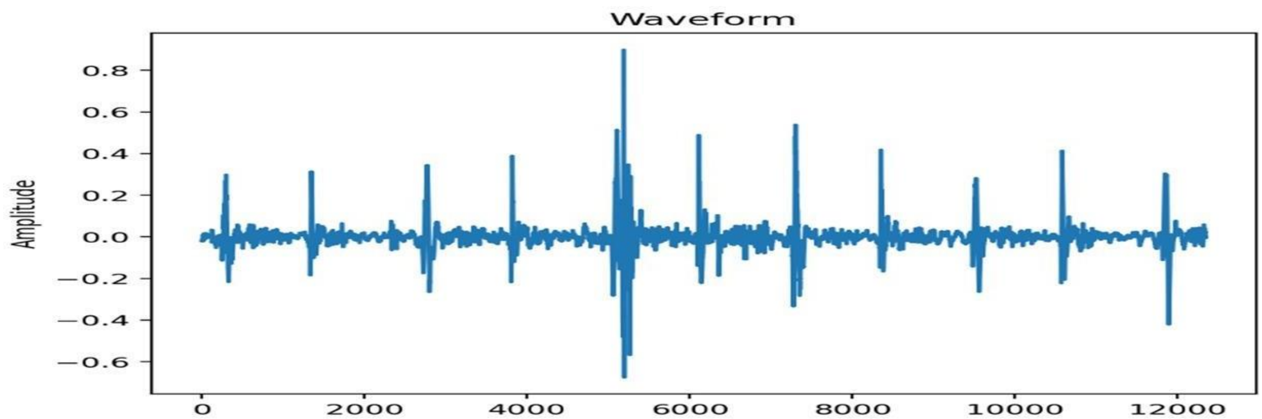

Figure 3. Waveform of Audio Data

On the other hand, due to the high dimensionality and variability of the raw waveform data, an analysis of the data directly presents challenges.It is common practice to convert audio data into other representations, such as spectrograms or Mel-Frequency Cepstral Coefficients (MFCCs), in order to meet the issues that are presented. A spectrogram is a visual depiction of the frequency content of an audio signal across time. It provides insights into the spectral properties of the sound by providing a visual representation of the frequency content. MFCCs, on the other hand, are able to capture the spectrum envelope of the audio signal by extracting elements that are similar to the way the human auditory system reacts to sound.

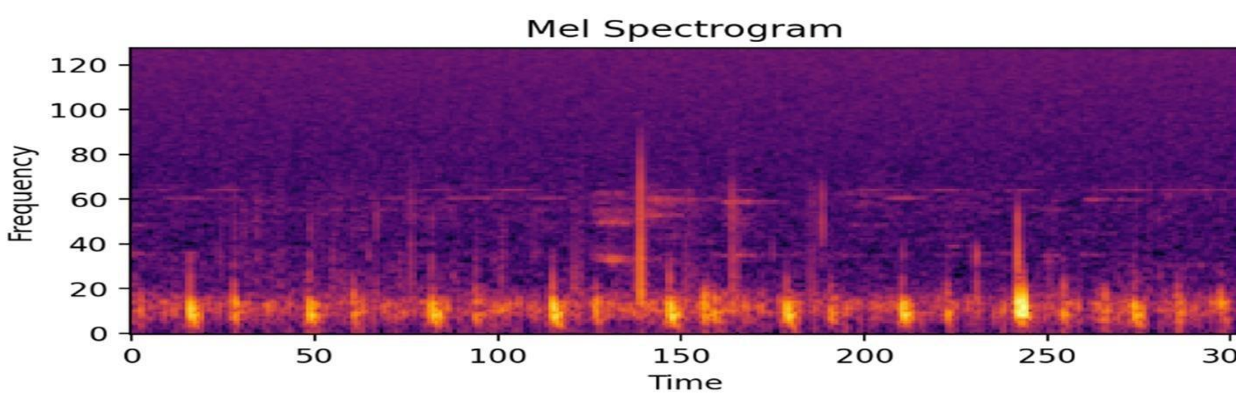

Figure 4. Mel Spectrogram of Audio Data

B.AUDIO SIGNAL PROCESSING

Audio signal processing for heart beat classification involves preprocessing and extracting meaningful features from heart sound recordings. This includes cleaning and segmenting the data, computing the signal envelope, applying filters for noise reduction, and generating spectrograms or extracting Mel-frequency cepstral coefficients (MFCCs) .This feature is particularly effective in capturing the spectral characteristics of an audio signal.

C.DATA AUGMENTATION

In the process of expanding a dataset, a method known as data augmentation is used. This approach involves applying different changes to existing information samples while maintaining the semantic meaning of the samples. In our heart beat sound classification project, we employed data augmentation techniques to expand our dataset and enhance the robustnessof our machine learning model. Specifically, we utilized white noise augmentation alongside other methods like time stretching and pitch shifting. With an initial dataset of 666 samples, we employed data augmentation techniques, including white noise augmentation, time stretching, and pitch shifting. By expanding our dataset to 5966 samples. White noise augmentation is effective because it simulates background noise commonly found in the heart sound recordings, making the model more resilient to noisy environments. Additionally, it helps prevent overfitting by introducing variability into the dataset and improves the model's ability to generalize to unseen scenarios. Overall, the inclusion of white noise augmentation contributes to the reliability and performance of our heart beat sound classification model.

D.RASPBERRY PI 4

We deployed the heart beat sound classification using deep learning project on a Raspberry Pi 4. By optimizing the model and converting it into a lightweight format compatible with Raspberry Pi's hardware constraints, we ensured efficient inference on the device. This enabled real-time classification of heart sounds directly on the Raspberry Pi, offering a portable and low-cost solution for health monitoring applications.

III.FLOWCHART OF THE SYSTEM

The flowchart illustrates a process, system, or algorithm that is used in computers. This is a graphical depiction of the actions that need to be carried out in a system, and it displays the steps in the sequence that they are to be carried out. It is used in the presentation of algorithm flow and in the communication of complicated processes via the usage of diagrams that are straightforward and simple to comprehend.

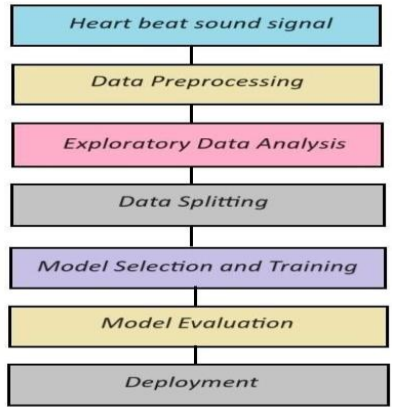

Figure 5: Flowchart Of The proposed System

IV.DATA COLLECTION

The data collection process for heart rate classification based on sound using deep learning involves a comprehensive and diverse approach. Audio recordings of heartbeats are gathered from reputable medical databases ensuring a rich and varied dataset. Collaborations with healthcare professionals, research institutions, and hospitals are initiated to obtain access to proprietary datasetsthat may offer insights into different heart conditions.The emphasis is on obtaining diverse and representative audio recordings of heartbeats to ensure the model's robustness and generalization.

V.DATA PRE-PROCESSING

Data pre-processing is meticulous and aims to prepare the collected audio dataset for effective model training. Rigorous cleaning procedures involve the removal of redundant or irregular data points, ensuring a high-quality dataset. Standardization measures are implemented to harmonize audio file formats, sample rates, and durations, promoting consistency across the dataset. Feature extraction becomes a sophisticated step, involving the identification and extraction ofintricate audio features that hold discriminative value for different heart conditions.

VI.EXPLORATORY DATA ANALYSIS

Exploratory Data Analysis (EDA) is a critical phase to gain a deep understanding of the dataset's characteristics. Visualizations such as sound waveforms, spectrograms, and distribution plots are employed to unveil patterns and trends within the audio data. This iterative process aids in uncovering the subtleties of normal and abnormal heart sounds, informing subsequent model development decisions.

VII.FEATURE EXTRACTION

Feature extraction is conducted with precision, employing advanced techniques such as signal processing to delve into the frequency components of heart sounds. Leveraging pre-trained deep learning models designed for audio analysis automates the extraction of pertinent features, reducing the dimensionality of the dataset. The aim is to create a feature-rich representation that enhances the model's ability to discern subtle variations associated with different heart conditions.

VIII.TRAINING AND TESTING THE MODEL

In the field of machine learning, the term "training a model" refers to the procedure of instructing a model to draw conclusions or make predictions based on the data that it is given. The model is able to generalize and arrive at predictions on new data that it has not before seen because it learns the patterns, associations, and characteristics that are included inside the training data as it is being trained. This is a fundamental step in supervised learning, where the model is provided with a labeled dataset, meaning that the correct output or target is known for each input.

We are able to split the dataset into two.The training set is a subset that is used to train a model, while the test set is a subset that is used to test your trained model.One of the metrics that may be used to evaluate classification models is accuracy. Accuracy may be defined informally as the percentage of predictions that our model was correct about. According to the official definition, accuracy is defined as follows:

$$Accuracy = \frac{Number\ of\ correct\ Predictions}{Total\ number\ of\ predictions} \tag{1}$$

IX.MODEL EVALUATION

Model evaluation is conducted with granularity, employing a suite of metrics tailored to classification tasks. Metrics such as accuracy, precision offer insights into the model's performance. Cross-validation techniques add robustness to the evaluation process, ensuring the model's reliability across different subsets of the data. Ethical considerations remain at the forefront, emphasizing privacy protection, informed consent, and compliance with healthcare regulations to uphold ethical standards in the handling of medical data throughout the model development lifecycle.

5. EXPERIMENTAL EVALUATION

The dataset comprises heart sound recordings labeled into five distinct categories: normal, extrastole, extrahls, artifact, and murmur. The class distribution indicates that the 'normal' category has the highest number of samples, followed by extrastole and extrahls, with artifact and murmur having slightly fewer samples. This balanced distribution, apart from the 'normal' category, suggests a diverse dataset useful for training heart sound classification models. The visualization helps in understanding the prevalence of each class within the dataset.

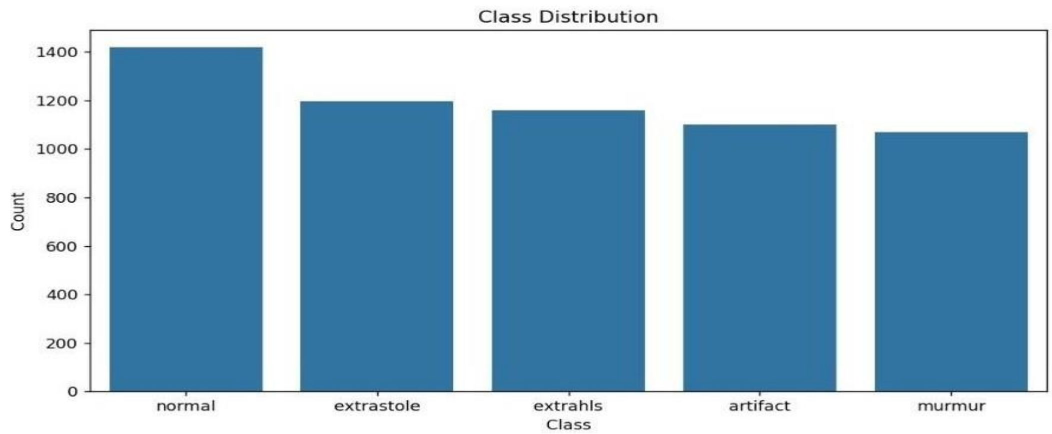

Figure 6.Class Distribution

Table 1:Observation done by using CNN model.

Aspects	**CNN**
Data Type	Suitable for spatially structured data
Feature Extraction	Hierarchical feature extractionusing convolutional filters
Representation	Process data in spatial domain(e.g., spectrograms)
Temporal Information	Limited capture of temporal dynamics
Model Complexity	Generally lower compared toRNNs
Training Efficiency	More computationally efficient, parallelizable
Suitability for Heart Beat Sound classification	Can be applied to spectrogram representations, may not capture temporal dynamics as effectively
Examples	Image classification, object detection

In this part, we will give the results of our experiment to classify the sounds of heartbeats, which was carried out using Streamlit and was carried out on a Raspberry Pi system. The purpose of this study was to categorize heart sounds into normal and pathological categories by using deep learning methods, more particularly Convolutional Neural Networks (CNNs), on a tiny portable system such as the Raspberry Pi system, which is yielding results that are equal to those of a typical desktop system. The Streamlit framework was utilized to create an interactive webapplication for deploying and showcasing the classification models. We developed an interactive web application using the Streamlit framework to deploy our heart beat sound classification models. The application allows users to upload their own heart sound recordings and receive real-time predictions on the classification of the heart sounds as normal or abnormal.

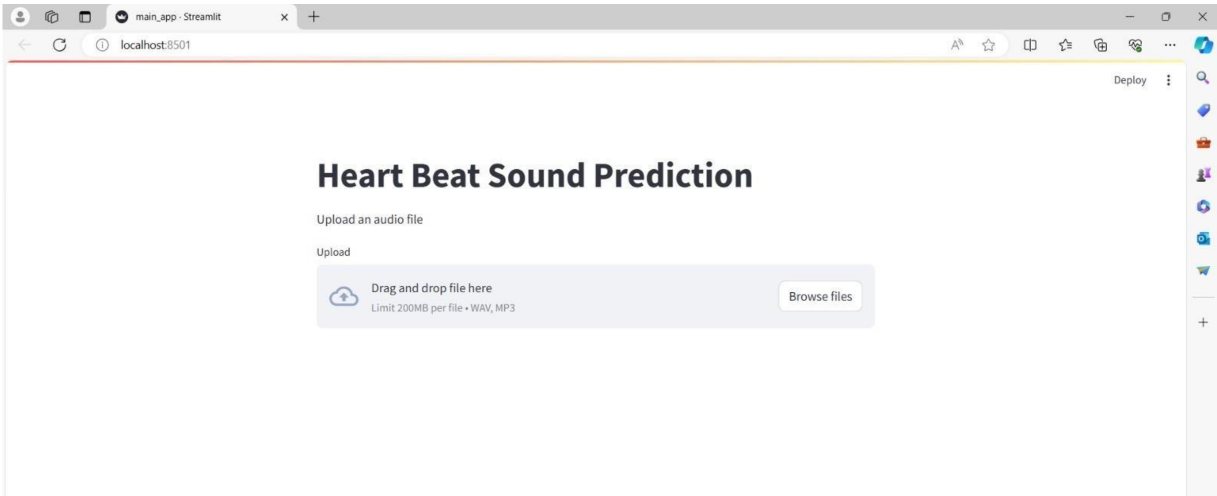

Figure 7: Heart Beat Sound Prediction Home page

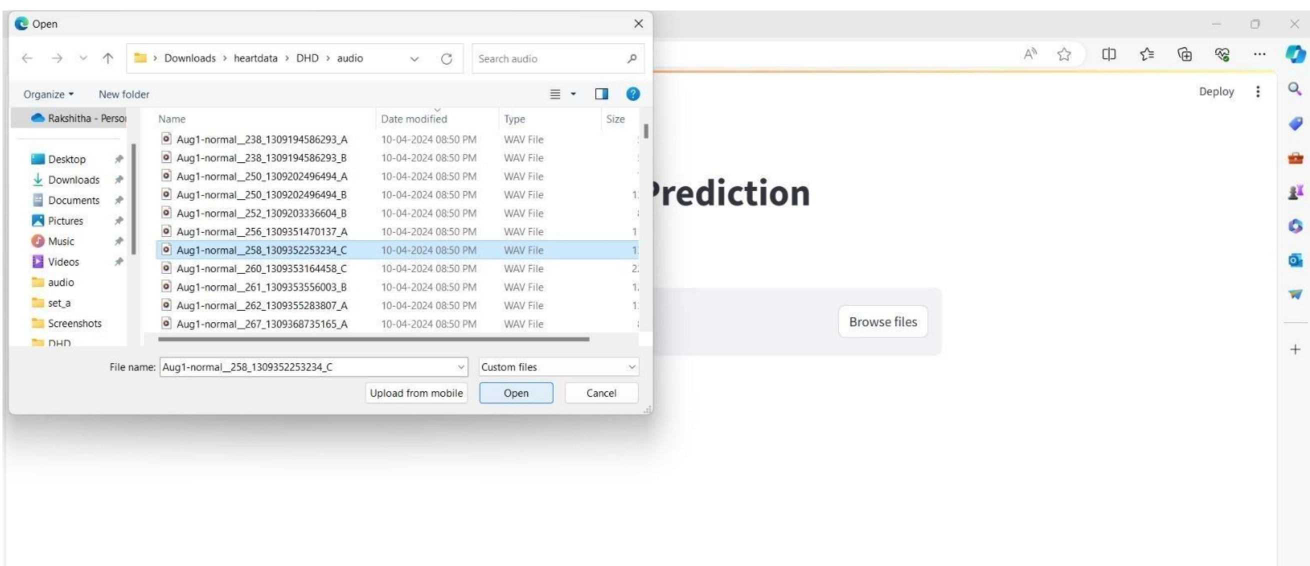

Figure 8: Selecting the audio files

The user interface of the Streamlit application features intuitive controls for uploading audio files, initiating model inference, and visualizing the classification results. We display the additional functionalities such as waveform and spectrograms of the uploaded audio files for further analysis.

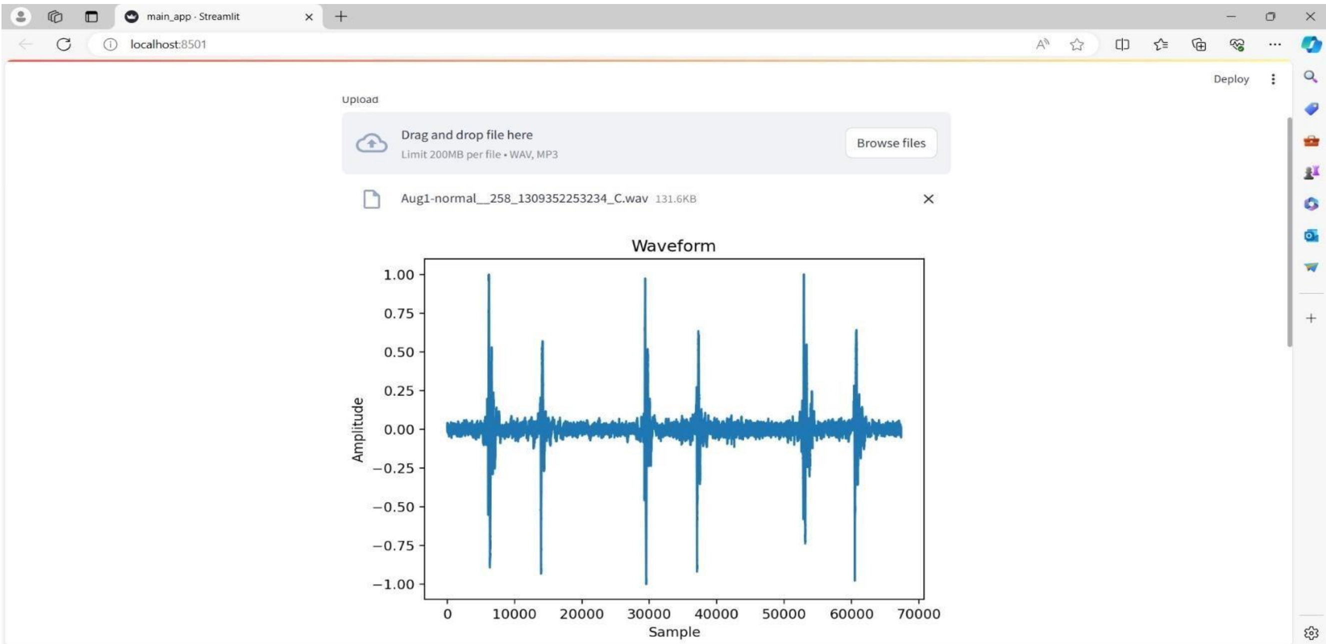

Figure 9: Waveform of Selected audio file

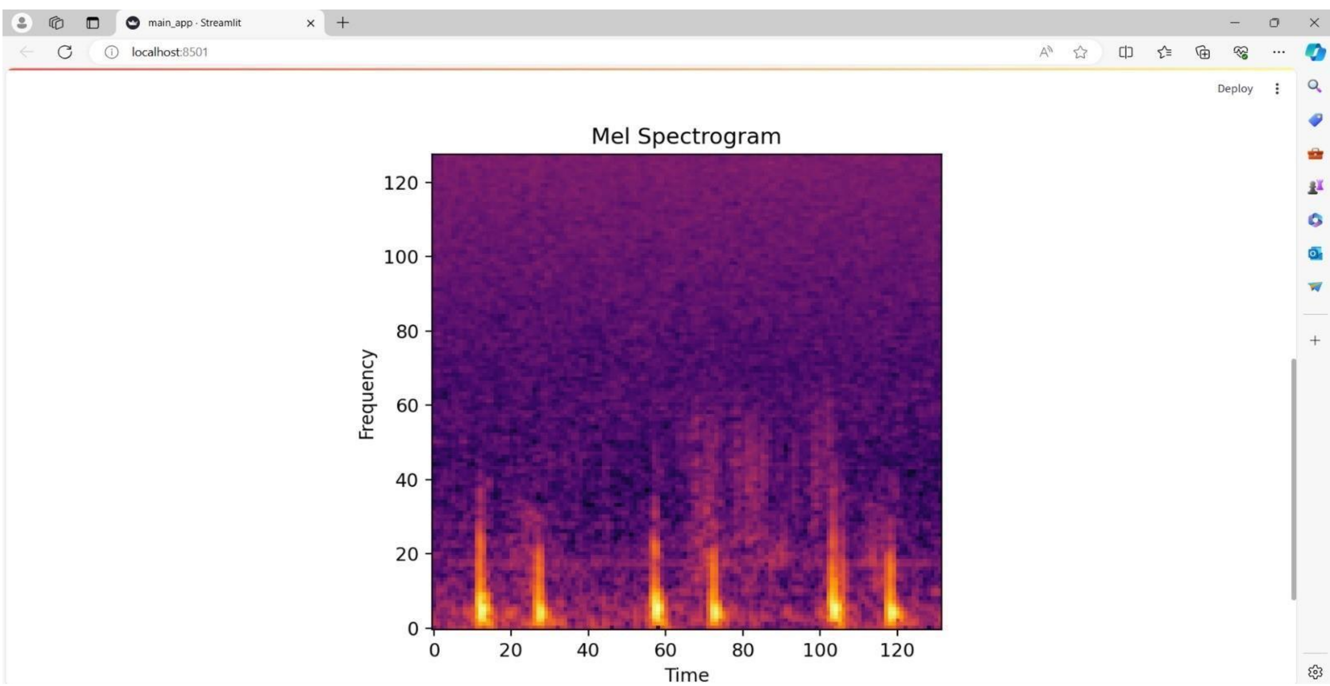

Figure 10: Spectrogram of Selected Audio file

Additionally, we have implemented a supplementary feature within the Streamlit application, creating an additional page dedicated to displaying detailed information about the predicted class in a new window. Users are presented with comprehensive insights into the classification results, and they have the option to download this information into a PDF format for further analysis and documentation.

CONCLUSION

In conclusion, this article represents a significant advancement in healthcare technology by introducing an automated solution for heart rate classification using sound signals on to the Raspberry Pi system. By employing Convolutional Neural Networks (CNN), the system achieves accurate classification of heart beat rates into multiple categories, including normal, murmur, extra heart sound, extrasystole, and artifact even on the Raspberry Pi system. The CNN achieves an accuracy of 95%. The CNN's higher accuracy of 95% suggests that it excels in capturing spatial features present in the sound signals with the limited computing resource. Bringing this model on Raspberry Pi gives the option of portability, ease of using by even a non technical person and very much cost effective system.

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