DEVELOPING A MACHINE LEARNING DRIVEN CARDIO ACOUSTIC ANALYZER FOR CARDIAC CONDITION DETECTION

A PROJECT REPORT

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PANIMALAR ENGINEERING COLLEGE

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BONAFIDE CERTIFICATE

Certified that this project report **DEVELOPING A MACHINE LEARNING DRIVEN CARDIO ACOUSTIC ANALYZER FOR CARDIAC CONDITION DETECTION** is the bonafide work of **ANANYAA R R [211421104019], GAYATHRI V [211421104074], LIKITHA R [211421104142]** who carried out the project work under my supervision.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION BY THE STUDENT

We **ANANYAA R R [211421104019], GAYATHRI V [211421104074], LIKITHA R [211421104142]** hereby declare that this project report titled **DEVELOPING A MACHINE LEARNING DRIVEN CARDIO ACOUSTIC ANALYZER FOR CARDIAC CONDITION DETECTION,** under the guidance of **Dr C. JACKULIN** is the original work done by us and we have not plagiarized or submitted to any other degree in any university by us.

ANANYAA R R

GAYATHRI V

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PROJECT COMPLETION CERTIFICATE

SATHYA SAI HEALTH SERVICES

MARCH 28, 2025

CERTIFICATE

This is to certify that Ms. **Ananyaa R R,** Ms. **Gayathri V**, Ms. **Likitha R,** ***B.E (Computer Science Engineering)*** students from Panimalar Engineering College, Chennai, has done their project work titled *"Developing an ML-Driven Cardio Acoustic Analyzer for Cardiac Condition Detection"* in our R&D department from January 2025 to March 2025 as part of their curriculum.

We have noticed that, during the period, they have shown keen interest in their stint and was also regular in attendance.

Dr. Maniksha K M

SATHYA SAI HEALTH SERVICES * CHENNAI

ABSTRACT

This project introduces a novel approach to heart sound analysis through the integration of machine learning models, within a user-friendly web application developed using the Django framework. The primary goal is to create a reliable and efficient system for classifying heart sounds from audio recordings, enabling the early detection and diagnosis of various cardiac conditions. The system processes and classifies heart sound recordings into several categories and provides detailed medical insights, including associated diseases, causes, prevention methods, etc. The Django framework serves as a powerful backend solution, ensuring smooth user interaction and secure data management. The system's ability to store and retrieve historical data from a centralized database enhances its usefulness in clinical settings, making it a valuable tool for healthcare professionals to monitor and assess heart health. By combining machine learning with a scalable web application, the project aims to facilitate the widespread adoption of automated heart sound analysis, ultimately contributing to improved patient outcomes and more efficient healthcare practices.

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
UI	User Interface
ERD	Entity Relationship Diagram

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

This project focuses on developing an AI-driven solution for cardiac condition detection by analysing heartbeat audio signals using machine learning techniques. Recurrent Neural Networks (RNNs) serve as the core model due to their ability to capture temporal dependencies in sequential data. The heartbeat recordings are processed using the Librosa library, which extracts key audio features necessary for accurate classification. RNNs have been chosen over Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures because of their superior efficiency in handling the given dataset. By leveraging these deep learning techniques, the system can identify subtle variations in heartbeat patterns, aiding in early diagnosis and continuous health monitoring.

To improve accessibility and ease of use, the project incorporates a Django-based web application. This platform enables healthcare professionals to upload heartbeat recordings seamlessly and receive analytical insights based on the trained machine learning model. The web interface provides a user-friendly experience, ensuring that even non-technical users can interact with the system efficiently.

This AI-driven approach to cardiac health monitoring not only improves diagnostic accuracy but also contributes to proactive healthcare management. By automating the analysis of heartbeat sounds, the system reduces the dependency on specialized medical expertise, making early detection of cardiac conditions more accessible. The combination of machine learning, signal processing, and web technologies offers a promising step toward AI-powered healthcare solutions, emphasizing both precision and ease of implementation.

1.2 PROBLEM DEFINITION

Early and accurate detection of cardiac conditions is crucial for improving patient outcomes. Traditional diagnostic methods, such as auscultation, heavily depend on a clinician's expertise, making them prone to errors, delays, and human bias. Manual heart sound analysis can be time-consuming, and factors like environmental noise, examiner skill level, and patient-specific variations further complicate accurate diagnosis. The lack of automation in conventional methods limits their scalability and efficiency, leading to delayed detection and intervention.

To address these challenges, this project develops a machine learning-driven cardiac acoustic analyser that automates heartbeat analysis and classification. By leveraging deep learning techniques and audio signal processing, the system extracts key acoustic features and classifies heart sounds into normal and abnormal categories. Using Recurrent Neural Networks (RNNs), the model captures temporal dependencies in heartbeats, ensuring more precise and reliable detection.

The goal is to enhance diagnostic accuracy, reduce reliance on specialized clinicians, and facilitate early detection of cardiac abnormalities. This AI-driven approach aims to revolutionize cardiac health monitoring, making it more accessible, efficient, and scalable for real-world healthcare applications.

CHAPTER 2

LITERATURE REVIEW

[1] Title: HeartWave: A Multiclass Dataset of HeartSounds for Cardiovascular Diseases Detection

The "HeartWave" dataset is a comprehensive collection of heart sound recordings encompassing nine distinct classes of common heart sounds associated with various cardiovascular diseases. This dataset aims to facilitate the development of AI-based tools for early detection of cardiovascular diseases, which are a leading cause of mortality worldwide. The dataset includes 864 recordings across five distinct classes of common heart sounds, representing a broad spectrum of valvular heart diseases, with a focus on diagnostically challenging cases. A notable feature of the dataset is its innovative multi label annotation system, capturing a diverse range of diseases and unique disease states. This enhances its utility for developing advanced machine learning models in automated heart sound classification and diagnosis.

The *HeartWave* dataset offers several advantages in the field of cardiovascular disease detection using AI. It provides a **comprehensive and diverse collection** of heart sound recordings, covering nine distinct classes, including normal and abnormal cases. With **864 high-quality recordings**, it enables the development of **machine learning models** for automated classification, facilitating **early diagnosis** of heart conditions. One of its key strengths is the **multi-label annotation system**, which captures overlapping disease states, enhancing the dataset's utility for advanced AI applications. Additionally, its **public availability** promotes open research and allows benchmarking against standardized data, contributing to the improvement of AI-driven diagnostics.

The dataset has some limitations that must be considered. Despite its **detailed classification**, the number of recordings (864) may be insufficient for training deep learning models without additional data augmentation. **Class imbalance** is another potential issue, as some disease categories might have fewer samples, leading to biased model predictions. Furthermore, the **quality of heart sound recordings** can vary due to external factors such as different stethoscope types and background noise, which may impact model performance. The dataset also lacks **patient demographic information** (such as age, gender, and medical history), which is crucial for **personalized diagnostics**. Lastly, while the dataset is valuable for research, AI models trained on it may face **generalization challenges** in real-world clinical environments, necessitating validation on larger and more diverse hospital datasets. Despite these drawbacks, *HeartWave* represents a significant step forward in leveraging AI for cardiac health research.

[2] Title: A Robust Deep Learning Framework Based on Spectrograms for Classification

The paper titled "A Robust Deep Learning Framework Based on Spectrograms for Heart Sound Classification" by Junxin Chen and colleagues presents an innovative approach to classifying heart sounds using deep learning techniques. The authors transform heart sound recordings into spectrograms, capturing both temporal and spectral features, and subsequently apply convolutional neural networks (CNNs) to these representations. This methodology leverages the strengths of CNNs in image recognition to effectively analyze the visual patterns within spectrograms, aiming to enhance the accuracy of heart sound classification.

One significant advantage of this framework is its ability to utilize spectrograms, which provide a rich representation of heart sounds by combining time and frequency information. This allows the model to capture intricate patterns that are crucial for distinguishing between normal and pathological heart sounds.

Additionally, by employing CNNs, the framework benefits from automated feature extraction, reducing the reliance on manual preprocessing and potentially leading to more robust and generalizable models.

However, there are certain limitations to consider. The performance of the model is heavily dependent on the quality and size of the training dataset; inadequate or unbalanced data can result in overfitting or biased predictions. Moreover, transforming heart sounds into spectrograms introduces additional computational complexity, which may pose challenges for real-time applications or deployment in resource-constrained environments. Despite these challenges, the proposed framework represents a promising advancement in the automated analysis of heart sounds, with the potential to improve early detection and diagnosis of cardiovascular diseases.

[3] Title: Heart Sound Analysis in Individuals Supported with Left Ventricular Assist Devices

The paper titled "Heart Sound Analysis in Individuals Supported with Left Ventricular Assist Devices" by Xinlin J. Chen et al. explores the feasibility of analyzing intrinsic heart sounds in patients with Left Ventricular Assist Devices (LVADs). The study collected precordial sound recordings from 17 LVAD recipients and utilized adaptive filtering techniques to mitigate device-generated noise, thereby isolating the patients' native heart sounds. The authors identified various acoustic signatures and established correlations between heart sound characteristics and the level of LVAD support, suggesting that heart sound analysis could serve as a non-invasive method for monitoring cardiac function in these patients.

The study demonstrates that, by effectively reducing LVAD-generated noise, intrinsic heart sounds can be analyzed, offering a non-invasive approach to monitor cardiac function in LVAD patients. Identifying specific acoustic signatures correlated with LVAD support levels provides valuable insights that could enhance patient management and early detection of potential complications.

The complexity of distinguishing between LVAD noise and intrinsic heart sounds requires sophisticated signal processing techniques, which may not be readily available in all clinical settings, potentially limiting the widespread adoption of this monitoring approach.

[4] Title: Neonatal Heart and Lung Sound Quality Assessment for Robust Heart and Breathing Rate Estimation for Telehealth Applications

The paper titled "Neonatal Heart and Lung Sound Quality Assessment for Robust Heart and Breathing Rate Estimation for Telehealth Applications" by Ethan Grooby et al. proposes an automated method to assess the quality of neonatal chest sound recordings, aiming to enhance the accuracy of heart rate (HR) and breathing rate (BR) estimations in telehealth settings. The study analyzed 88 ten-second chest sound recordings from 76 preterm and full-term infants, with six annotators independently evaluating signal quality, detectable heartbeats, and breathing periods. A dynamic binary classification model was developed using 187 heart sound features and 182 lung sound features, followed by feature selection, class balancing, and hyper parameter optimization. The model's performance was validated by comparing automatic HR and BR estimations against manual annotations, demonstrating improved reliability in vital sign monitoring for neonatal telehealth applications.

Objective Quality Assessment: The proposed method offers an objective and automated evaluation of chest sound recordings, reducing reliance on subjective assessments and enhancing consistency in telehealth monitoring. Improved Vital Sign Estimation: By accurately assessing signal quality, the approach enhances the precision of HR and BR estimations, which is crucial for effective neonatal monitoring and timely medical interventions. Telehealth Integration: The automated nature of the system facilitates seamless integration into telehealth platforms, enabling remote monitoring and potentially expanding access to neonatal care in underserved regions.

Limited Dataset: The study's sample size of 88 recordings may not fully represent the variability in neonatal chest sounds, potentially limiting the generalizability of the findings. Feature Complexity: The use of a large number of features (187 for heart sounds and 182 for lung sounds) could lead to overfitting, necessitating careful feature selection and validation on larger datasets. Real-World Applicability: While the method shows promise, its effectiveness in diverse clinical environments with varying noise levels and recording conditions requires further investigation to ensure robustness.

[5] Title: A Comprehensive Overview of Heart Sound Analysis Using Machine Learning Methods

The paper titled "A Comprehensive Overview of Heart Sound Analysis Using Machine Learning Methods" by M. F. A. B. Hamza and colleagues provides an in- depth examination of the application of machine learning techniques to heart sound analysis. The authors highlight how intelligent computational techniques and machine learning algorithms have enhanced the accuracy of cardiac disease detection and reduced detection time.

The detailed comparison between classical machine learning and contemporary deep learning approaches, aiding researchers in understanding the evolution and current state of the field. Additionally, the survey is complemented by a publicly accessible repository that aggregates relevant academic articles, methodologies, and datasets, serving as a valuable resource for both new and seasoned researchers.

While it thoroughly covers the period up to its publication, the rapidly evolving nature of machine learning applications means that more recent developments might not be included. Furthermore, the survey predominantly focuses on technical advancements, potentially underrepresenting practical challenges such as clinical integration and real- world applicability. Despite these limitations, the paper stands as a significant contribution, offering a detailed synthesis of machine learning's role in heart sound analysis and guiding future research endeavors in this critical area of healthcare technology.

[6] Title: Towards Domain Invariant Heart Sound Abnormality Detection Using Learnable Filterbanks

The paper titled "Towards Domain Invariant Heart Sound Abnormality Detection Using Learnable Filterbanks" by Ahmed Imtiaz Humayun et al. addresses the challenge of domain variability in heart sound abnormality detection systems. The authors propose a novel Convolutional Neural Network (CNN) architecture that incorporates time- convolutional (tConv) units emulating Finite Impulse Response (FIR) filters. These learnable filterbanks are designed to adapt to different recording conditions, sensors, and environments, thereby enhancing the robustness of phonocardiogram (PCG) signal analysis. Evaluations on publicly available multi-domain datasets demonstrated that this approach outperforms existing methods, achieving up to an 11.84% relative improvement in mean accuracy (MAcc) for binary classification tasks.

Enhanced Robustness: The learnable filterbank architecture effectively mitigates the adverse effects of domain variability, leading to more reliable heart sound abnormality detection across diverse recording conditions. Improved Performance: The proposed method surpasses top-scoring systems in the literature, achieving significant improvements in sensitivity, specificity, F1 score, and Macc. Practical Applicability: By addressing sensor and environment-induced variability, this approach paves the way for deploying automated cardiac screening systems in diverse and underserved communities.

Computational Complexity: The integration of learnable filterbanks into the CNN architecture may increase computational requirements, potentially limiting real- time application in resource-constrained settings. Generalization Concerns: While the method shows promise, its effectiveness across all possible domain variations requires further validation to ensure consistent performance. Data Dependency: The approach relies on the availability of diverse multi-domain datasets for training to achieve domain invariance, which may not always be accessible.

[7] Title: A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era

The paper titled "A Comprehensive Survey on Heart Sound Analysis in the Deep Learning

Era" by Z. Ren, Y. Chang, et al., provides an extensive overview of the application of deep learning techniques to heart sound analysis, focusing on studies published between 2017 and 2022. Recognizing the limitations of classical machine learning methods in handling large-scale data, the authors highlight how deep learning architectures have enhanced the extraction of effective representations in this domain.

One of the key advantages of this survey is its timely update on the integration of deep learning in heart sound analysis, filling the gap left by earlier reviews conducted before 2017. The authors provide a comprehensive comparison between classical machine learning and contemporary deep learning approaches, aiding researchers in understanding the evolution and current state of the field. Additionally, the survey is complemented by a publicly accessible repository that aggregates relevant academic articles, methodologies, and datasets, serving as a valuable resource for both new and seasoned researchers.

However, the survey also has certain limitations. While it thoroughly covers the period up to 2022, the rapidly evolving nature of deep learning applications means that more recent developments might not be included. Furthermore, the survey predominantly focuses on technical advancements, potentially underrepresenting practical challenges such as clinical integration and real-world applicability.

Despite these limitations, the paper stands as a significant contribution, offering a detailed synthesis of deep learning's role in heart sound analysis and guiding future research endeavors in this critial area of healthcare technology.

[8] Title: PCGmix: A Data-Augmentation Method for Heart-Sound Classification

The paper titled "PCGmix: A Data-Augmentation Method for Heart-Sound Classification" by David Susič, Anton Gradišek, and Matjaž Gams introduces an innovative approach to enhance heart sound classification through data augmentation. The PCGmix method involves segmenting and reassembling phonocardiogram (PCG) recordings, incorporating meticulous interpolation to preserve essential diagnostic features crucial for cardiovascular disease detection. Empirical assessments on publicly available datasets demonstrated that PCGmix outperforms traditional time-series augmentation techniques, particularly when training data is limited. Notably, the method achieved comparable accuracy to non- augmented approaches, even when trained on datasets that were 31% to 69% smaller.

PCGmix effectively enhances model performance by expanding the training dataset, which is particularly beneficial in scenarios with limited data availability.The method preserves critical diagnostic features during augmentation, ensuring the integrity of heart sound characteristics essential for accurate classification. By outperforming traditional augmentation techniques, PCGmix demonstrates its potential to improve the robustness and reliability of heart sound classification models.

The segmentation and reassembly process of PCGmix may introduce artifacts if not carefully implemented, potentially affecting model performance. The method's effectiveness relies on the quality of the original recordings; poor-quality data could limit the benefits of augmentation. As a novel approach, PCGmix may require additional validation across diverse datasets to establish its generalizability and effectiveness in various clinical settings.

[9] Title: Blind Monaural Source Separation on Heart and Lung Sounds Based on Periodic-Coded Deep Autoencoder

The paper titled "Blind Monaural Source Separation on Heart and Lung Sounds Based on Periodic-Coded Deep Autoencoder" by Kun-Hsi Tsai et al. introduces a novel approach to separate heart and lung sounds from a single-channel recording. The authors propose a Periodicity-Coded Deep Autoencoder (PC-DAE) that leverages the distinct periodic characteristics of heartbeats and respiratory cycles to achieve unsupervised separation of these sounds. This method addresses the challenge of overlapping frequency ranges between heart and lung sounds, which complicates traditional separation techniques. The PC-DAE model was evaluated on both simulated datasets and real-world recordings, demonstrating its effectiveness in isolating heart and lung sounds without the need for paired training data.

Unsupervised Learning: The PC-DAE does not require paired training data of mixed and pure sounds, making it practical for real-world applications where obtaining isolated heart or lung sounds is challenging. Enhanced Diagnostic Accuracy: By effectively separating heart and lung sounds, the method facilitates more accurate auscultation, aiding in the diagnosis of cardiovascular and respiratory diseases. Robustness: The model demonstrated strong performance across various datasets, indicating its potential adaptability to different recording conditions and patient populations.

Computational Complexity: The deep learning architecture of PC-DAE may require significant computational resources, which could limit its implementation in resource- constrained settings. Dependence on Signal Quality: The effectiveness of the separation process relies on the quality of the input recordings; noisy or poor-quality signals may hinder the model's performance. Limited Clinical Validation: While the method shows promise, extensive clinical validation is necessary to confirm its utility and reliability in diverse clinical environments.

[10] Title:Multi-Feature DecisionFusion Network for Heart Sound Abnormality Detection and Classification

The paper *"Multi-Feature Decision Fusion Network for Heart Sound Abnormality Detection and Classification"* by Haobo Zhang et al. introduces MDFNet, a deep learning framework designed for heart sound classification. It consists of a Multi- dimensional Feature Extraction (MFE) module and a Multi-dimensional Decision Fusion (MDF) module to capture spatial and temporal patterns in heart sounds. The model also integrates attention mechanisms to focus on key heart sound features and applies data augmentation techniques to enhance robustness. With this approach, MDFNet achieves high accuracy in both binary and multi-class heart sound classification tasks.

A major advantage of MDFNet is its ability to extract and integrate multi- dimensional heart sound features, improving classification performance. The use of attention mechanisms helps the model focus on relevant heart sound segments, increasing diagnostic accuracy. Additionally, the proposed data augmentation technique addresses challenges related to cardiac cycle segmentation, making the model more adaptable to real-world scenarios. Empirical results demonstrate its effectiveness, with high accuracy and F1-scores in both binary and multi-class classification.

Despite its strengths, MDFNet's performance depends heavily on the quality and diversity of the training data, making it susceptible to biases if the dataset is unbalanced. The computational complexity of the model may pose challenges for real-time applications, particularly in low-resource settings. Additionally, deploying MDFNet in clinical environments requires further validation on large- scale, diverse datasets to ensure its reliability. These factors highlight the need for further optimizations to improve practical usability.

2.1 LITERATURE REVIEW TABLE

TABLE 2.1: SUMMARY OF LITERATURE REVIEW

S .NO	YEAR	PAPER DETAILS	JOURNAL DETAILS	APPROACH	OUTCOME
1	2023	Sami Alrabie, et al.”HeartWave: Multiclass Dataset of Heart Sounds for Cardiovascular Diseases Detection”	IEEEAccess Volume 11 2023	The authors developed the "HeartWave" dataset by collecting, preprocessing, and labeling heart sound recordings using advanced signal processing techniques.	The dataset enables robust machine learning model development for cardiovascular disease detection, supporting advancements in non-invasive cardiac diagnostics.
2	2023	Chen, Junxin ,et al. “A Robust Deep Learning Framework Based on Spectrograms for Heart Sound Classification”	IEEE/ACM Transactions on Computational Biology and Bioinformatics Volume: 21 Issue: 4, July-Aug. 2024	The authors employ a deep learning model that processes heart sound signals transformed into spectrograms, enabling the model to effectively capture temporal and frequency domain features.	The proposed framework demonstrates improved performance in classifying heart sounds, suggesting its potential as a reliable tool for early detection of cardiac conditions.

S. NO	YEAR	PAPER DETAILS	JOURNAL DETAILS	APPROACH	OUTCOME
3	2021	Xinlin J. Chen, et al.”Heart Sound AnalysisinIndividuals Supported With Left Ventricular Assist Devices”	IEEE Transactionson Biomedical Engineering Volume: 68 Issue: 10 October 2021	Thepaperanalyzesheart sounds of patients with Left Ventricular Assist Devices(LVADs)using advanced signal processing to identify uniqueacousticpatterns influencedbythe device.	The study uncovers distinct acoustic signatures,aidinginnon-invasive monitoring of LVAD function and detecting potential complications.
4	2020	Ethan Grooby et al. “Neonatal Heart and Lung Sound Quality Assessment for Robust Heart and Breathing Rate Estimation for Telehealth Applications”	IEEE Journal of Biomedical and Health Informatics Volume: 25 Issue: 12 December 2021	The paper proposes an automated method to assess the quality of neonatal chest sound recordings, improving heart and breathing rate estimations for telehealth.	The approach enhances the accuracy of heart and breathing rate estimations from noisy neonatal sounds, supporting better remote monitoring in neonatal care.

S .NO	YEAR	PAPER DETAILS	JOURNAL DETAILS	APPROACH	OUTCOME
5	2024	M. F. A. B. Haza, et al. "A Comprehensive Overview of Heart Sound Analysis Using Machine Learning Methods"	IEEE Access Volume: 12	The paper reviews machine learning methods for processing and classifying heart sounds, emphasizing feature extraction and classification algorithms for cardiovascular diagnosis.	Machine learning improves accuracy in heart sound classification, but better datasets and advanced techniques are needed for more reliable results.
6	2020	Ahmed Imtiaz Humayun, et al. "Towards Domain Invariant Heart Sound Abnormality Detection Using Learnable Filterbanks "	IEEE Journal of Biomedical and Health Informatics Volume: 24 Issue: 8 August 2020	A CNN layer with time-convolutional (tConv) units that function like Finite Impulse Response (FIR) filters, allowing for backpropagation of filter coefficients.	The proposed method surpasses state-of-the-art systems, improving heart sound abnormality detection accuracy by up to **11.84% MAcc** on multi-domain datasets.

S .NO	YEAR	PAPER DETAILS	JOURNAL DETAILS	APPROACH	OUTCOME
7	2024	Z. Ren, Y. Chang, et al. “A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era”	IEEE Computational Intelligence Magazine Volume: 19 Issue: 3 2024	The paper reviews deep learning techniques for analyzing heart sounds, focusing on signal processing, classification, and addressing data challenges.	Deep learning improves heart sound analysis accuracy but requires better datasets and standardized, interpretable models for broader use.
8	2024	David Susič, et al. “PCGmix: A Data-Augmentation Method for Heart-Sound Classification”	IEEE Journal of Biomedical and Health Informatics Volume: 28 Issue:11 November 2024	A data augmentation technique that generates synthetic heart sound samples by combining segments of existing phonocardiograms to improve training diversity for classification models.	The method enhances the accuracy and robustness of heart sound classification models, enabling better detection of cardiac abnormalities.

S .NO	YEAR	PAPER DETAILS	JOURNAL DETAILS	APPROACH	OUTCOME
9	2020	Kun- Hsi Tsai, et al. “Blind Monaural Source Separation on Heart and Lung Sounds Based on Periodic- Coded Deep Autoencoder”	IEEE Journal of Biomedical and Health Informatics Volume: 24 Issue:11 November 2020	The paper introduces a periodic-coded deep auto encoder for blind monaural source separation, isolating heart and lung sounds from single-channel recordings without prior source knowledge.	The method achieves high accuracy and signal quality in separating heart and lung sounds, enhancing clinical assessments and automated sound analysis.
10	2023	Haobo Zhang et al. “Multi- Feature Decision Fusion Network for Heart Sound Abnormality Detection and Classification”	IEEE Journal of Biomedical and Health Informatics Volume: 28 Issue: 3 March 2024	A Multi-Feature Decision Fusion Network that integrates various features extracted from heart sound recordings. This network combines multiple decision-making processes to enhance the accuracy and reliability.	The proposed framework demonstrated improved performance in identifying and classifying abnormal heart sounds, contributing to more effective early diagnosis of cardiovascular conditions.

CHAPTER 3
THEORETICAL BACKGROUND

3.1 IMPLEMENTATION ENVIRONMENT

Anaconda Navigator is a desktop graphical user interface (GUI) included in the Anaconda® distribution, designed to simplify the management of conda packages, environments, and channels without requiring command-line commands. It enables users to search for packages on Anaconda.org or a local Anaconda Repository and provides a seamless way to launch applications. Anaconda itself, developed by Continuum Analytics, is a Python distribution that comes preinstalled with numerous libraries essential for data science, machine learning, and scientific computing. The implementation of this project is carried out in Jupyter Notebook, a widely used interactive computing environment that seamlessly integrates code execution, data analysis, and visualization. This platform facilitates an iterative workflow, making it ideal for tasks such as data preprocessing, feature extraction, model training, and evaluation. By leveraging Jupyter Notebook, the project benefits from its ability to run Python code alongside markdown documentation and visual outputs, ensuring clarity and reproducibility. It is flexible to modify and test code dynamically, analyzing the results in real time.

3.2 SYSTEM ARCHITECTURE

Fig 3.1 illustrates the entire process of machine learning-based heart sound analysis, starting from data collection to deployment. Initially, heartbeat sound data is gathered from public datasets like Kaggle or medical equipment. The raw data undergoes preprocessing steps such as noise removal, signal normalization, segmentation, and feature extraction (e.g., MFCCs). Additionally, exploratory data analysis helps in addressing imbalances and identifying patterns.

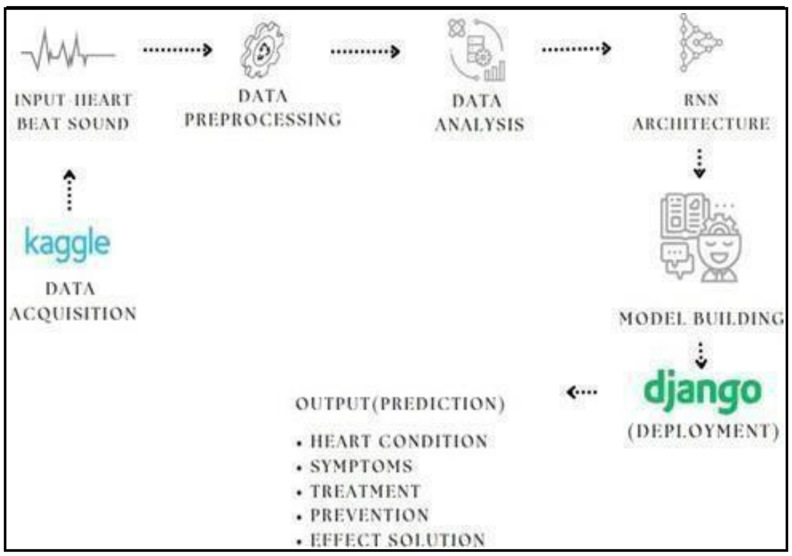


Fig 3.1 Architecture Diagram

The core of the system is an RNN architecture, which has demonstrated superior accuracy compared to LSTM and GRU for this application. The RNN is trained to classify heart sounds and predict possible cardiac conditions. After training, the model generates outputs such as disease forecasts, preventive actions, and customized remedies. Finally, the trained model is integrated into a Django web application, allowing users to upload heart sound recordings, receive real-time predictions, and access insights through an intuitive interface. This machine learning-driven approach enhances early detection and diagnosis of cardiac disorders.

3.3 PROPOSED METHODOLOGY

Utilizes Recurrent Neural Network (RNN) architectures to analyse and classify heartbeat audio signals for medical diagnostics. Processes recorded heartbeat sounds by extracting relevant audio features. Employs a trained RNN model to categorize heartbeat audio signals. Provides a Django-based interface for users to: Seamlessly upload audio recordings. Receive instant classification feedback. Access a comprehensive database of recorded results. Aims to enhance early detection of heart conditions, improving diagnostic accuracy and patient outcomes.

3.1.1 DATASET DESCRIPTION

TABLE 3.1: DATASET

S.NO.	TYPE OF CLASSIFICATION	FILE FORMAT	LENGTH OF THE AUDIO	NUMBER OF AUDIOS
1	Artifact	WAV File	~1-12secs	200
2	Extrahls	WAV File	~1-15secs	200
3	Extrastole	WAV File	~1-10secs	200
4	Murmur	WAV File	~1-13secs	200
5	Normal	WAV File	~1-15secs	324
6	Unlabel	WAV File	~1-10secs	200

Table 2 depicts that the dataset consists of six categories of heart sound recordings, all stored in WAV format. Each recording varies in length, ranging from approximately 1 to 15 seconds**.** The dataset includes 200 samples each for Artifact, Extrahls, Extrastole, Murmur, and Unlabel classes, while the Normal class has 324 recordings. This structured dataset is essential for training machine learning models to classify heart sounds accurately and detect potential cardiac conditions.

3.2.2 INPUT DESIGN (UI)

Fig 3.2 illustrates the user registration interface, where users are required to enter their first name, last name, email, username, password, and confirm password. All fields are mandatory, ensuring data completeness before proceeding.

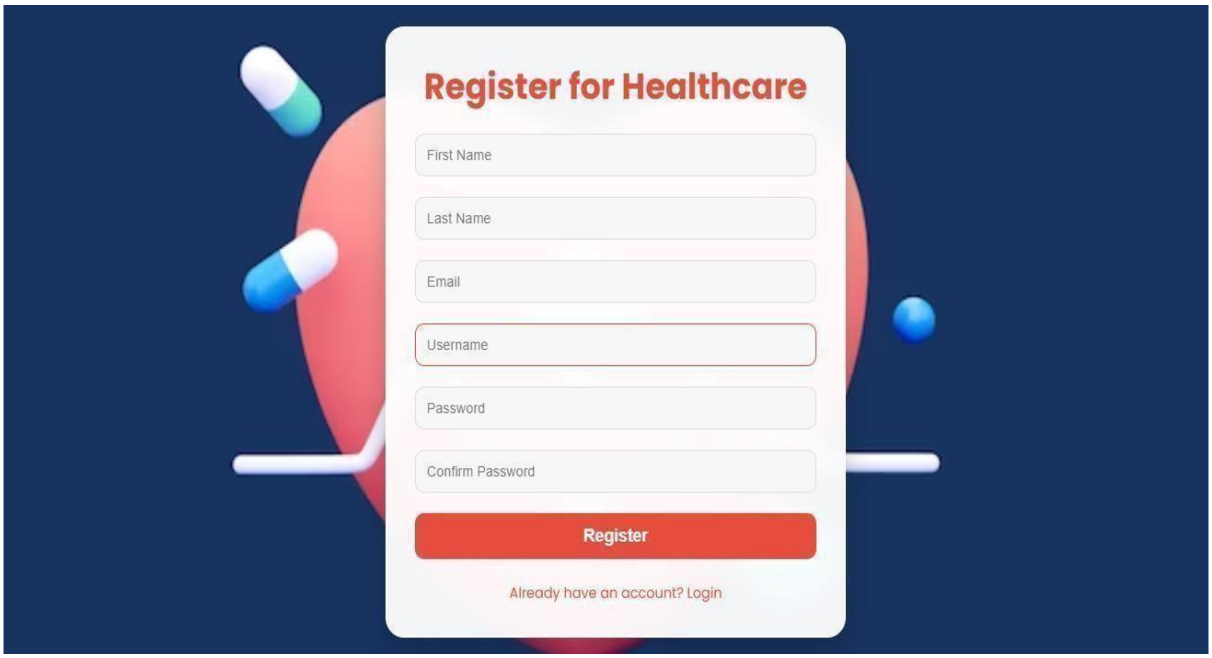


Fig 3.2 User Registration Page

Upon filling in the required details, users must click the "Register" button to create an account. This step serves as the initial phase of the authentication process, enabling users to gain access to the system by logging in after successful registration.

Fig 3.3 illustrates the user login page of a web application Once users complete registration, they can log in by entering their username and password. Upon successful login, they gain access to the features and functionalities of the web application

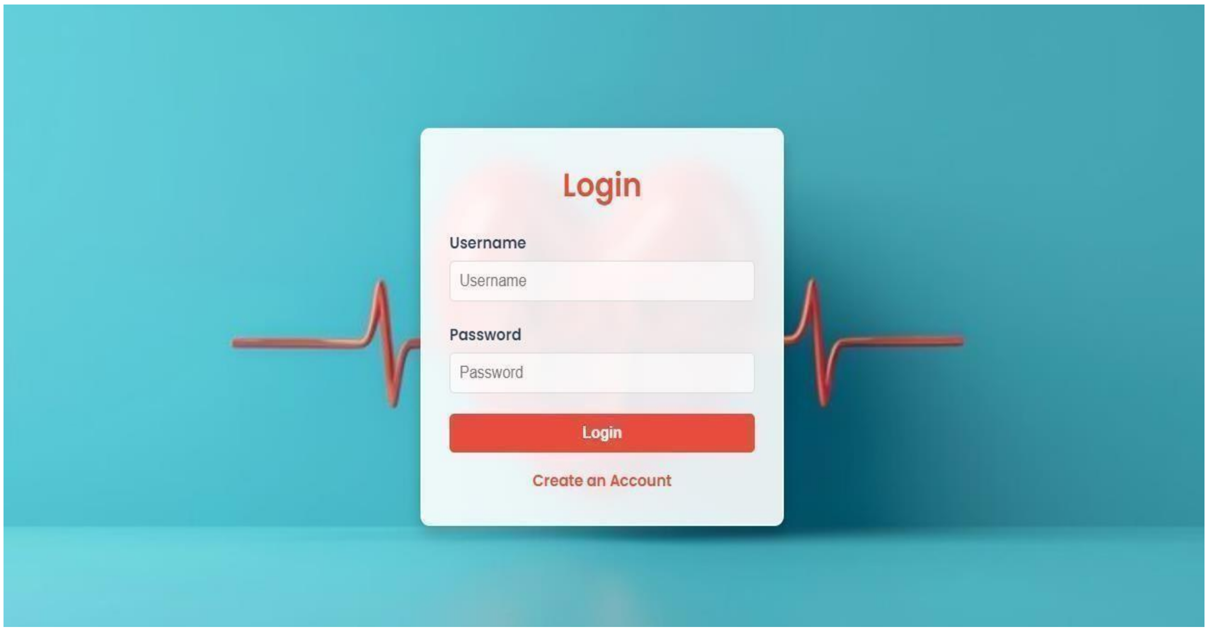


Fig 3.3 User Login Page

The image displays the user login page, where users can securely access the web application by entering their registered username and password. This page ensures authentication and data protection, allowing only authorized users to proceed. After successful login, users can navigate through various features, such as uploading audio files, analyzing results, and viewing their previous records. The interface is designed for ease of use, with clear input fields and validation mechanisms to prevent incorrect logins. Additionally, options for password recovery and account management may be provided for enhanced usability.

3.3.3 MODULE DESIGN

I. USE CASE DIAGRAM

In the given use case diagram, the system represents a web-based application designed for cardiac condition analysis based on audio inputs. The user interacts with the system through several functionalities. Initially, the user can register within the web application to create an account, after which they can log in to access personalized features. Upon authentication, the user is allowed to upload audio recordings—such as heart sounds— for analysis. Additionally, the user can access their database**,** which stores previously uploaded audio files and corresponding analysis results.

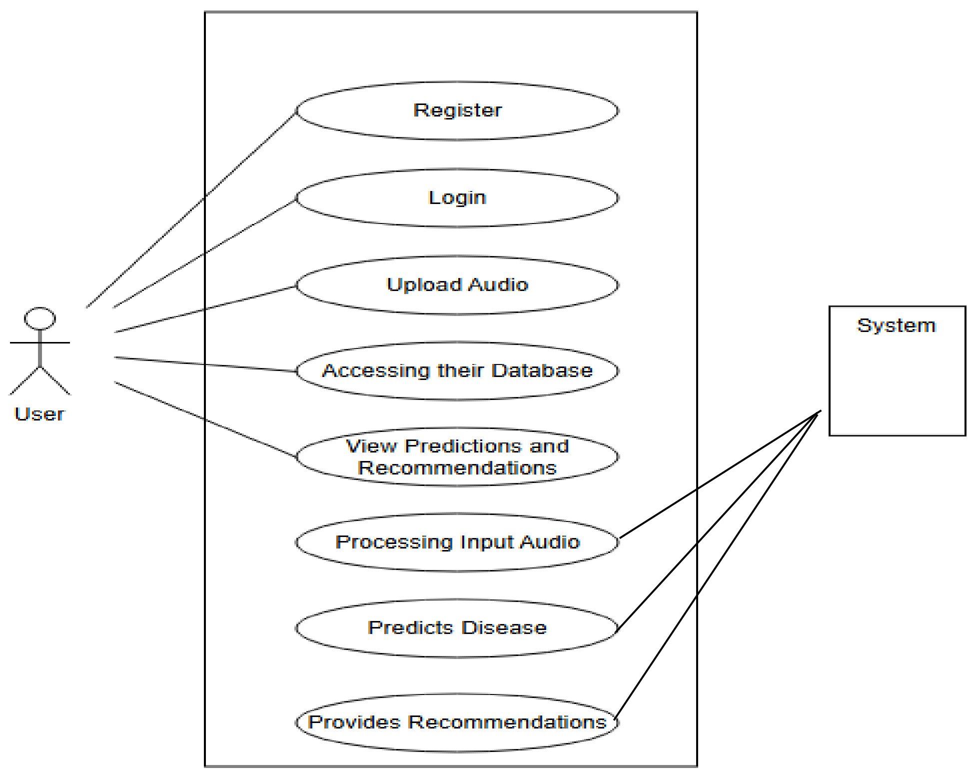


Fig 3.4 Use Case Diagram

Once the user uploads an audio file, the system analyzes sound patterns using machine learning techniques to predict potential cardiac conditions. Based on the results, it provides recommendations, including preventive measures or medical consultation suggestions, ensuring an efficient and accurate health analysis process.

II. CLASS DIAGRAM

Fig 3.5 illustrates the overall architecture of the project, beginning with audio data extraction under data analysis.

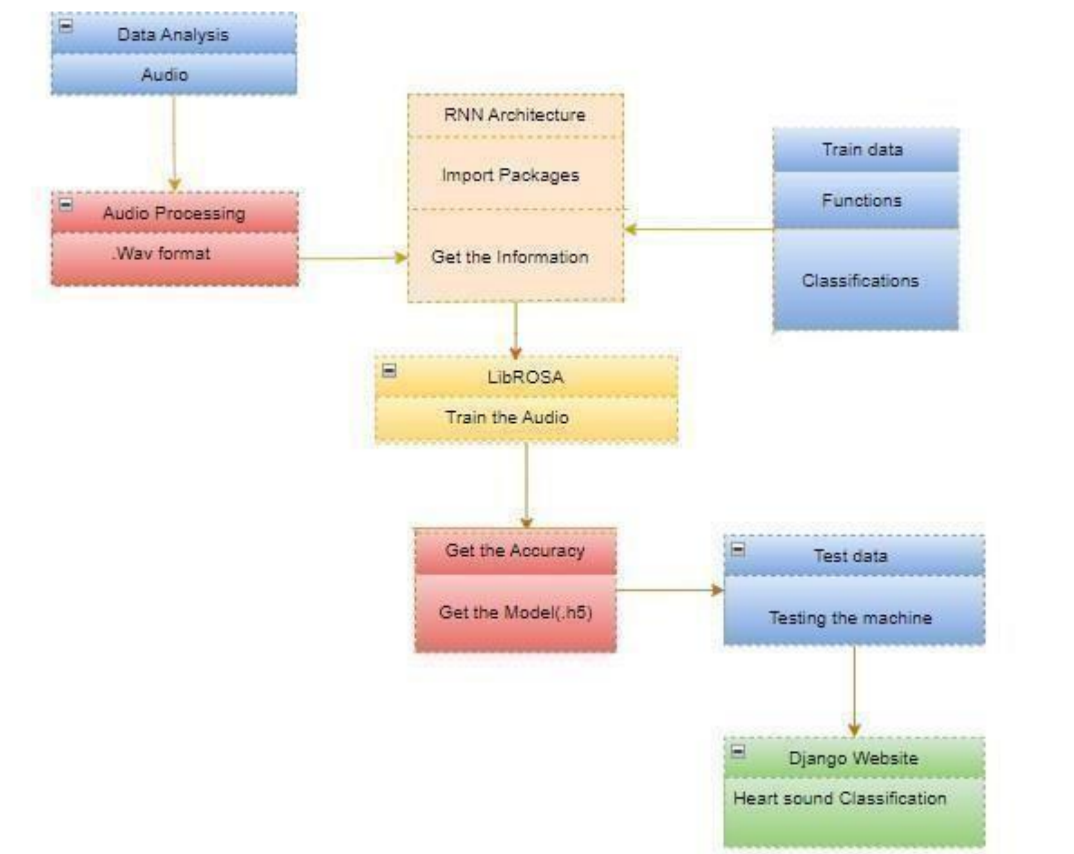


Fig 3.5 Class Diagram

The audio is preprocessed using the WAV format, followed by feature extraction through the Librosa library. The preprocessed data is then fed into an RNN (Recurrent Neural Network) architecture for training. Once the model achieves satisfactory accuracy, it undergoes testing. Finally, the trained model is deployed on a Django web application, where it classifies heart sounds and provides predictions based on the analyzed audio.

III. ACTIVITY DIAGRAM

Fig 3.6 outlines the process flow starting from dataset collection, followed by preprocessing steps that include preliminary analysis and calculation of dataset information.

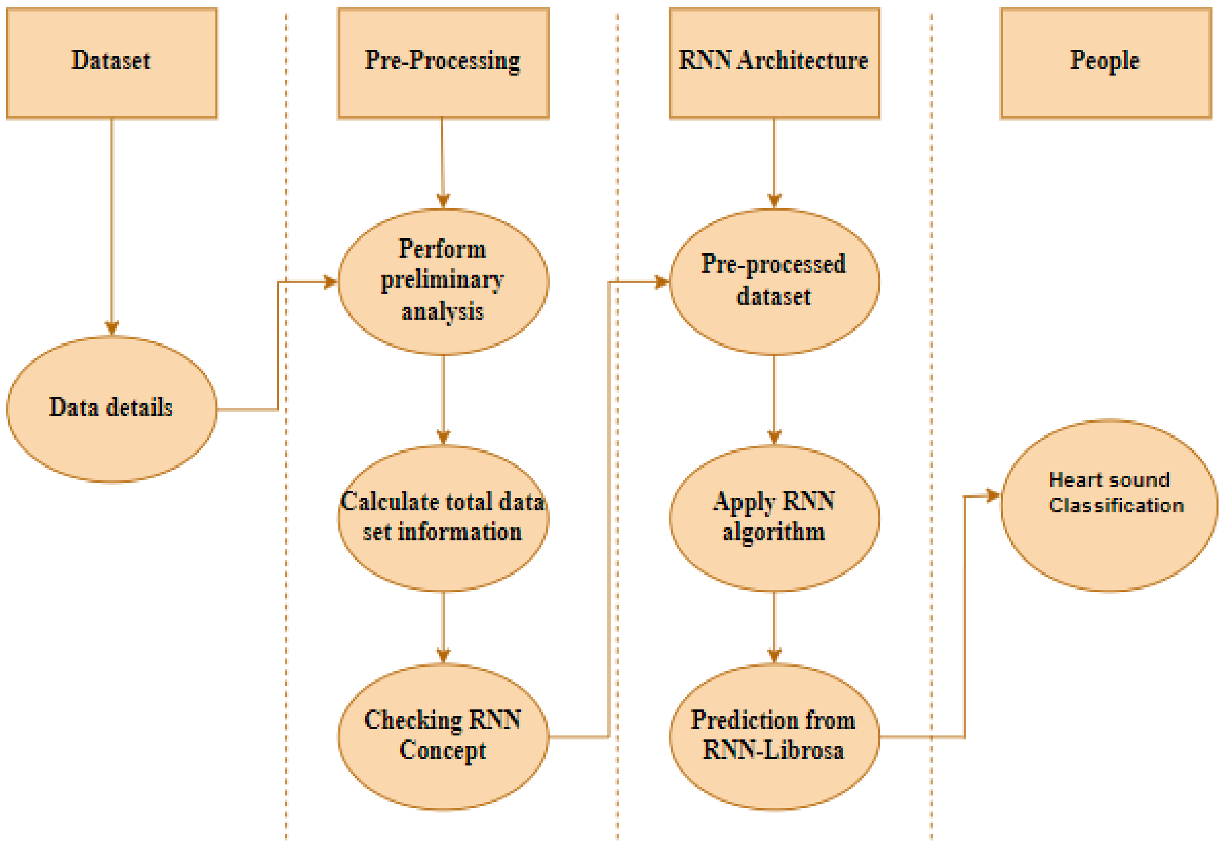


Fig 3.6 Activity Diagram

The system then checks the RNN concept and applies the RNN architecture. After preprocessing the data, the RNN algorithm is applied, followed by prediction generation using the Librosa library. Finally, the user is presented with heart sound classifications based on the predictions made by the model.

IV. SEQUENCE DIAGRAM

Fig 3.7 begins with the report data being dispatched from the dataset and moving into the past data section for validation. Once the data is verified as valid, the tuning model applies predictions using the RNN method.

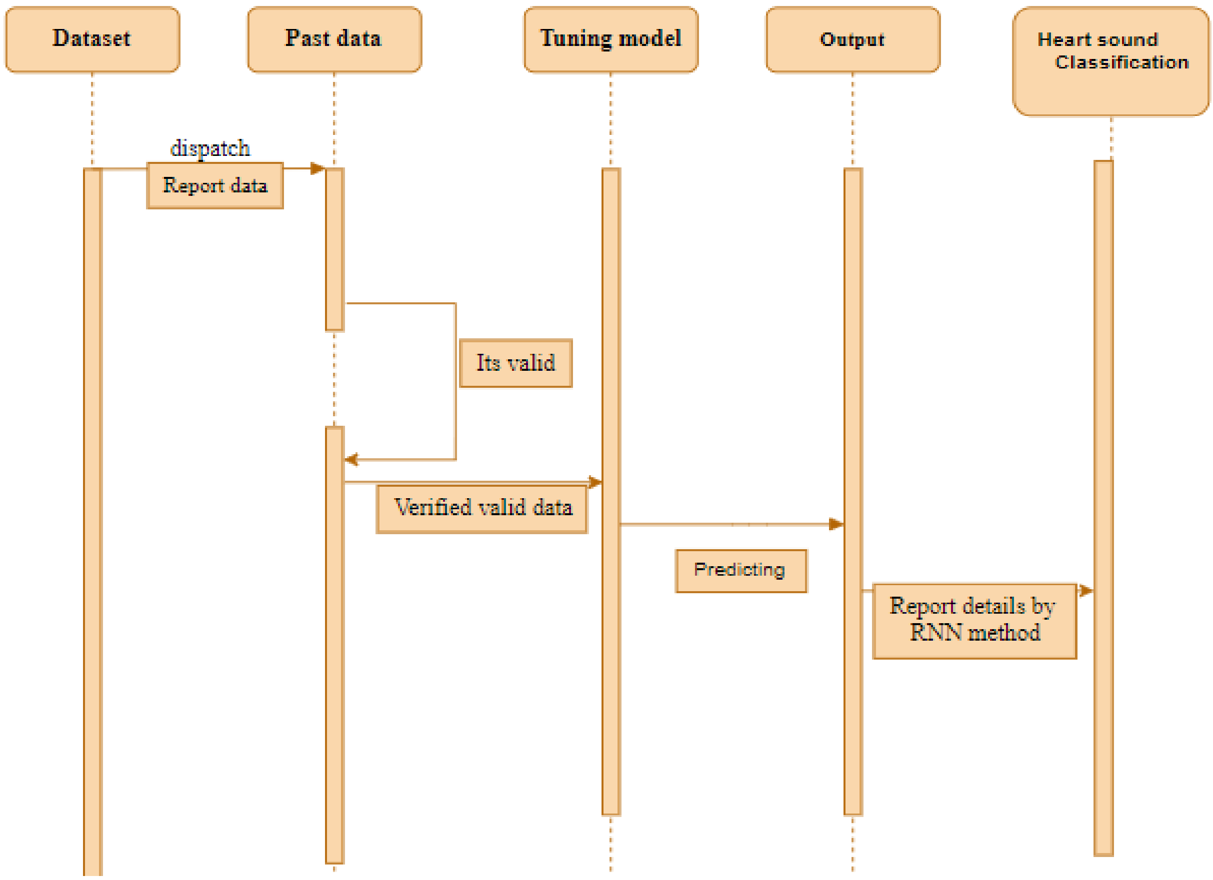


Fig 3.7 Sequence Diagram

Finally, the predicted output and all report details are displayed to the user. This sequence ensures that only verified data is processed and classified for heart sound predictions.

V. DFD LEVEL 1

Fig 3.8 outlines the process where users upload audio files into the cardiac disease prediction system. The system then performs data preprocessing, utilizing the trained model for analysis.

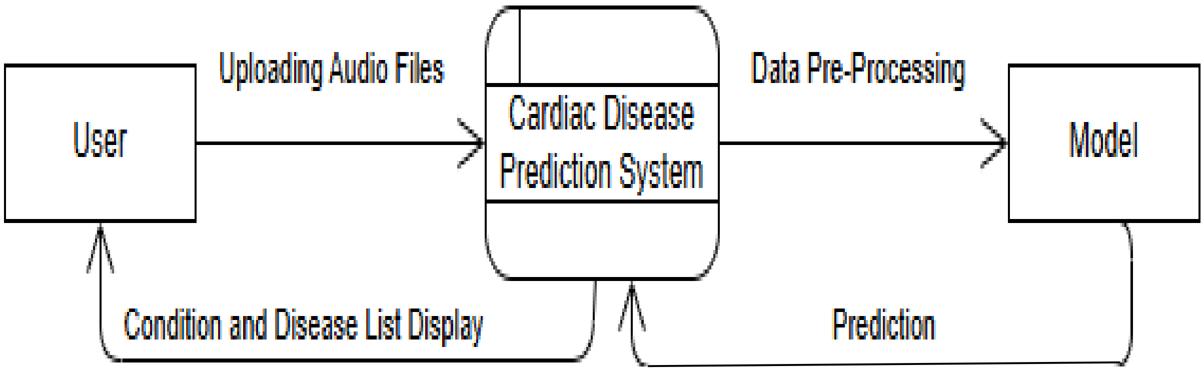


Fig 3.8 Data Flow Diagram

Once the analysis is complete, the model generates predictions regarding the heart condition and disease. The results, including the predicted disease and associated conditions, are displayed to the user, offering actionable insights based on the heart sound analysis. The Level 1 Data Flow Diagram provides a structured representation of the cardiac disease prediction system, detailing its key processes. Users begin by uploading heart sound recordings, which undergo preprocessing steps such as noise reduction and feature extraction. The system then applies a trained Recurrent Neural Network (RNN) model to analyse the audio data, identifying patterns and anomalies. The results, including the predicted heart condition and possible disease classification, are presented to the user. This process enables early detection and monitoring, assisting both individuals and healthcare professionals in assessing cardiac health.

VI. ENTITY RELATIONSHIP DIAGRAM (ERD)

Fig 3.9 represents the flow of data from the Kaggle dataset for audio classification. Initially, both RNN and LSTM models are compared, with RNN demonstrating higher efficiency.

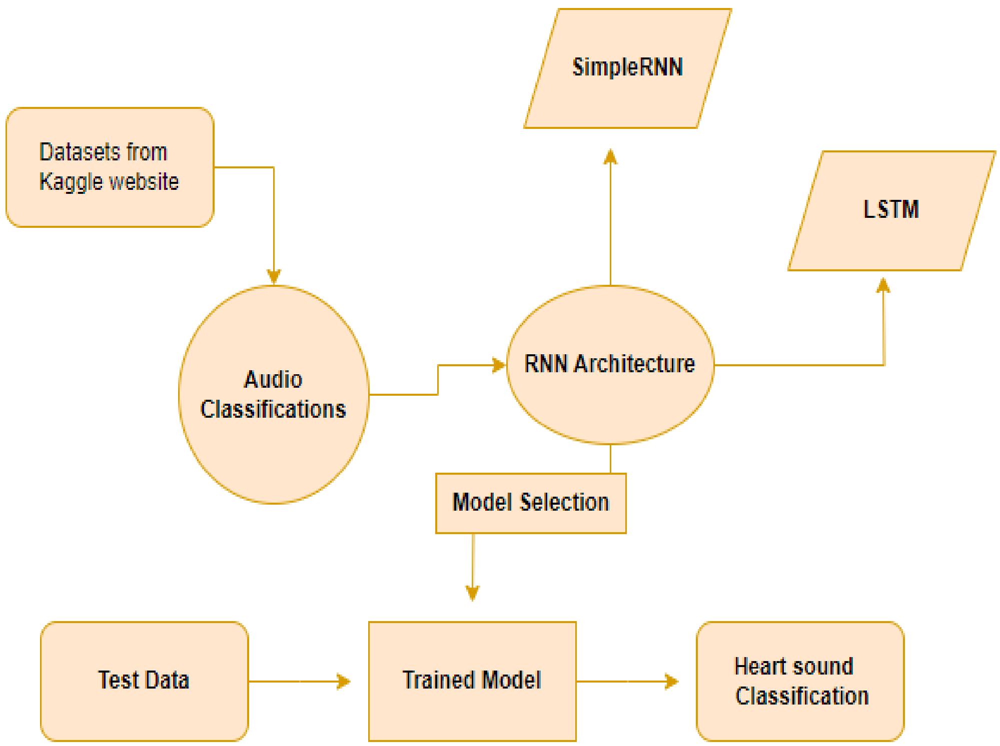


Fig 3.9 Entity Relationship Diagram

Consequently, the system is trained using the RNN architecture, followed by testing and evaluation. Upon successful training, the model is deployed for real-time cardiac disease predictions based on heart sound analysis.

CHAPTER 4

SYSTEM IMPLEMENTATION

4.1 RECURRENT NEURAL NETWORKS (RNN)

Recurrent Neural Networks (RNNs) are a type of neural network designed specifically for processing sequential data, where the order of the data points is crucial. Unlike traditional feedforward neural networks, RNNs have an inherent ability to use their internal state (or memory) to process sequences of inputs. This memory is updated at each time step, allowing the network to "remember" information from previous time steps and use it to influence future predictions or outputs. The architecture of an RNN consists of a single layer of recurrent units, which receive both the current input at time *t* and the hidden state from the previous time step $ht-1$. The hidden state is updated using a non-linear activation function like *tanh* or ReLU, and the output at each time step is calculated based on this updated state. Mathematically, the process can be described by the following equations:

$$ht=f(Wih.xt+Whh.ht-1+bh)\ ,\ yt=Who.ht+bo \qquad (4.1)$$

In Equation 4.1 hidden state of the process contains:

- *xt* is the input at time *t*,
- *ht* is the hidden state at time *t*,
- *Yt* is the output at time *t*,
- *Wih,Whh,Who* are weight matrices, and
- *bh,bo* are bias terms.

The key idea in RNNs is that the hidden state *hth_t*ht carries information from the previous time steps, enabling the network to understand temporal dependencies in sequential data. RNNs are typically trained using Backpropagation Through Time (BPTT), where the gradients are calculated by unrolling the network through all time steps and applying the standard backpropagation algorithm. However, RNNs suffer from the vanishing gradient problem, where the gradients can become very small when propagated over many time steps, making it difficult for the network to learn long-term dependencies. This issue arises because the gradients tend to shrink as they are back propagated through each time step, preventing the model from learning effective representations of long-range dependencies. Additionally, RNNs can also face the exploding gradient problem, where gradients become excessively large, leading to instability during training. Despite these challenges, RNNs have been used in a variety of applications, such as speech recognition, language modeling, and time series forecasting, where the order of the data plays a critical role.

4.2 LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) networks are a special type of Recurrent Neural Network (RNN) designed to overcome the limitations of standard RNNs, especially in handling long-term dependencies in sequential data. The LSTM architecture was introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997 to address the vanishing gradient problem inherent in traditional RNNs. Unlike basic RNNs, LSTMs utilize a more complex structure with multiple gates that control the flow of information, making them capable of preserving and modifying memory over long sequences. The key components of an LSTM are the cell state and three gates: the forget gate, the input gate, and the output gate.

Forget Gate: This gate determines what portion of the previous cell state $Ct-1$ should be discarded. It outputs a value between 0 and 1 using a sigmoid function, where 0 means "forget entirely" and 1 means "retain fully":

$$ft=\sigma(Wf.[ht-1,xt]+bf \tag{4.2}$$

Thus, Equation 4.2 deals with the function of Forget Gate.

Input Gate: The input gate decides how much of the new information from the current time step xt should be added to the cell state. It also uses a sigmoid function to regulate the amount of new information to store:

$$it=\sigma(Wi.[ht-1,xt]+bi) \tag{4.3}$$

Thus, Equation 4.3 deals with the function of Input Gate.

Cell State Update: The new cell state is computed by adding new candidate values $C\sim t$, which are generated using the input gate. This is controlled by the sigmoid output of the input gate, dictating how much new information should be included:

$$C\sim t=tanh(WC.[ht-1,xt]+bC) \qquad (4.4)$$

Thus, Equation 4.4 deals with the Candidate value.

The cell state Ct is then updated by combining the previous cell state $Ct-1$ and the new candidate values, regulated by the forget and input gates:

$$Ct=ft.Ct-1+it.C\sim t \qquad (4.5)$$

Thus, Equation 4.5 deals with the function of Cell State Update.

Output Gate: The output gate determines what part of the cell state Ct will be output as the hidden state *hth_t*ht for the current time step. It uses a sigmoid activation and the current cell state to compute the final output:

$$ot=\sigma(Wo.[ht-1,xt]+bo) \qquad (4.6)$$

Thus, Equation 4.6 deals with the function of Output Gate.

The hidden state ht is then calculated by applying a tanh function to the cell state, followed by multiplication with the output gate value:

$$ht=ot.tanh(Ct) \qquad (4.7)$$

Thus, Equation 4.7 deals with the final hidden state value.

The cell state Ct serves as the long-term memory, and the gates control how information is added, forgotten, or outputted. This ability to selectively forget or retain information allows LSTMs to handle long-range dependencies much better than traditional RNNs. LSTMs are trained using Backpropagation Through Time (BPTT), similar to RNNs, but with more stable gradients due to the gating mechanism. LSTMs have proven to be highly effective for tasks that require the model to remember information over extended periods, making them a cornerstone of modern deep learning in sequential data processing.

CHAPTER 5

RESULTS & DISCUSSION

5.1 PERFORMANCE PARAMETERS / TESTING

TABLE: 5.1 TESTING

TEST CASE ID	TEST CASE ACTION TO BE PERFORMED	EXPECTED RESULT	ACTUAL RESULT	PASS/FAIL
1	User navigates to the registration page and enters valid credentials to log in.	User should be successfully logged inand redirected to the home page.	User logged in successfully and redirected to the home page.	Pass
2	On the home page, user clicks the Database button.	User should be redirected to a page displaying their uploaded heartbeat sound files.	User redirected to the database page with uploaded heartbeat sound files.	Pass
3	On the home page, user clicks the Input button.	User should be redirected to a file upload page.	User successfully navigated to the file upload page.	Pass

4	User uploads a valid heartbeat sound file (.wav, .mp3).	File should be uploaded successfully, and a confirmation message should be displayed.	File uploaded successfully	Pass
5	After uploading, the system processes the file.	System should select the best model based on accuracy and continue processing.	Best model selected and file processed successfully.	Pass
6	System predicts the heart disease based on the best-performing model.	Accurate prediction result should be displayed.	Prediction displayed successfully.	Pass
7	The system displays disease details, symptoms, effects, dietary, and activity recommendations.	Relevant information based on the prediction should be displayed clearly.	Disease information displayed correctly.	Pass
8	User logs out from the system.	The user should be logged out and redirected to the login page.	User logged out successfully and redirected to the login page.	Pass

5.1 RESULTS & DISCUSSION

TABLE 5.2: ACCURACY ANALYSIS OF THE ALGORITHMS

CLASSIFIER	ACCURACY
RNN	94. 0
LSTM	93. 0
GRU	88. 0

Comparing RNN, LSTM, and GRU identified RNN as the most efficient architecture for this task, offering high accuracy at lower computational cost. Deep learning approaches outperformed traditional methods by learning complex patterns in heartbeat data. Integration with Django provided a user-friendly interface for audio uploads and real-time predictions, enhancing accessibility and enabling early heart disease detection.

The implementation of the heartbeat sound classification model using SimpleRNN architecture yielded promising results in accurately analyzing heartbeat sounds. The model effectively extracted meaningful audio features using the Librosa library and demonstrated high classification accuracy in distinguishing different heartbeat patterns.

The SimpleRNN-based approach successfully addressed the challenges associated with heartbeat sound classification, offering a lightweight yet powerful solution for analyzing cardiac signals. By leveraging deep learning, the model was able to uncover intricate patterns in heart sounds that traditional methods might overlook. Furthermore, the Django integration ensured that the technology is accessible, making it a valuable tool for early heart disease detection and diagnosis.

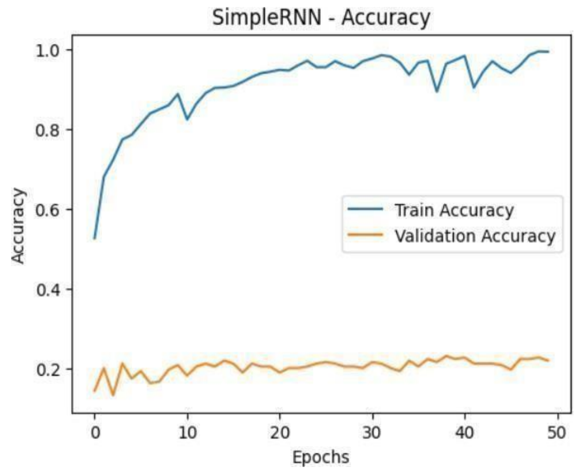


Fig 5.1 Sub Plot of Simple RNN-Accuracy

Comparative analysis showed that RNN achieved the best balance between accuracy and computational efficiency, making it the preferred architecture for this task. Key performance metrics such as accuracy, precision, recall, and F1- score confirmed the model's reliability in detecting abnormal heartbeats.

The integration with Django enabled real-time predictions, providing users with an intuitive platform to upload heartbeat recordings and receive instant diagnostic insights. The system's responsiveness and accuracy make it a valuable tool for early detection of cardiovascular anomalies, potentially aiding healthcare professionals in timely diagnosis and intervention.

Further analysis of the model's generalization capability revealed that it performs consistently well across different datasets, making it suitable for real-world applications. The ability of the RNN model to effectively classify heartbeat sounds across various conditions underscores its robustness and reliability. Additionally, the model's performance suggests that deep learning can significantly enhance automated cardiac diagnosis compared to traditional signal processing techniques.

CHAPTER 6

CONCLUSION & FUTURE WORKS

CONCLUSION

In this project, we compared LSTM and RNN architectures for analyzing heartbeat sounds using the Librosa library. RNN demonstrated higher efficiency, leading to its selection for our implementation. The model effectively classified various heartbeat types based on extracted audio features, showcasing the potential of deep learning in biomedical signal processing. Integration with Django provided a seamless interface for users to upload audio files and receive real-time predictions, emphasizing the practical applicability of this research in clinical settings.

FUTURE WORKS

1. Develop a hybrid model combining RNN with advanced techniques like attention mechanisms.
2. Expand the dataset with diverse heartbeat sounds for better generalization.
3. Integrate visualizations for improved interpretability of results.
4. Explore wearable device integration for real-time monitoring.
5. Explore GRU layers for performance enhancement.

APPENDICES

A.1 SDG GOALS

GOAL 3 **- Good Health and Well Being**

A.2 SOURCE CODE

```
import librosa
import librosa.display
import matplotlib.pyplot as plt
import IPython.display as ipd # Load the audio file audio_data, sr =
librosa.load(audio_fp)
# Trim silence from the beginning and end
audio_data, _ = librosa.effects.trim(audio_data) # Display the audio
ipd.display(ipd.Audio(audio_data, rate=sr))
# Plot the waveform plt.figure(figsize=(15, 5)) plt.plot(librosa.times_like(audio_data),
audio_data) plt.title('Waveform of Audio') plt.xlabel('Time (s)') plt.ylabel('Amplitude'
plt.show() import
librosa
import librosa.display
import matplotlib.pyplot as plt
import IPython.display as ipd # Load the audio file
audio_fp = 'E:/IYYAPPAN_OWN 2024-2025/AUDIO CLASSIFICATIONS
PROJECTS/vechile_audio_classifications/dataset/train/Cars/Car_Passing_Sound_Effect
s_2.wav'
audio_data, sr = librosa.load(audio_fp) #Trim silence
audio_data, _ = librosa.effects.trim(audio_data) # Display the audio
ipd.display(ipd.Audio(audio_data, rate=sr))
# Plot the waveform
plt.figure(figsize=(15, 5))
plt.plot(librosa.times_like(audio_data), audio_data) plt.title('Waveform of Audio')
```

```
plt.xlabel('Time  (s)')
plt.ylabel('Amplitude')
plt.show()
import librosa.display
import matplotlib.pyplot as plt import
numpy as np
# Load the audio file
audio_data, sr = librosa.load(audio_fp) # Trim silence
audio_data, _ = librosa.effects.trim(audio_data) # Plot the spectrogram
plt.figure(figsize=(15, 5))
D = librosa.amplitude_to_db(librosa.stft(audio_data), ref=np.max) librosa.display.specshow(D,
sr=sr, x_axis='time', y_axis='log') plt.title('Spectrogram')
plt.colorbar(format='%+2.0f dB') plt.show() import
librosa.display
import matplotlib.pyplot as plt # Load the audio file audio_data, sr
= librosa.load(audio_fp) # Trim silence audio_data, _ =
librosa.effects.trim(audio_data)
# Compute chroma features
chroma = librosa.feature.chroma_stft(y=audio_data, sr=sr) # Plot chroma feature
plt.figure(figsize=(15, 5))
librosa.display.specshow(chroma, sr=sr, x_axis='time', y_axis='chroma') plt.title('Chroma
Feature')
plt.colorbar() plt.show()
import librosa.display
import matplotlib.pyplot as plt # Load the audio fi
audio_data, sr = librosa.load(audio_fp) #Trimsilence
audio_data, _ = librosa.effects.trim(audio_data) # Compute Mel spectrogram
mel_spectrogram = librosa.feature.melspectrogram(y=audio_data, sr=sr, n_mels=128,
fmax=8000) # Plot Mel spectrogram plt.figure(figsize=(15, 5))
```

```
librosa.display.specshow(librosa.power_to_db(mel_spectrogram, ref=np.max), sr=sr, x_axis='time',
y_axis='mel', fmax=8000)
plt.title('Mel Spectrogram') plt.colorbar(format='%+2.0f dB')
plt.show()
import librosa
import matplotlib.pyplot as plt # Load the audio file
audio_data, sr = librosa.load(audio_fp) # Trim silence
audio_data, _ = librosa.effects.trim(audio_data) # Compute zero-crossing rate
zero_crossings = librosa.feature.zero_crossing_rate(audio_data) # Plot zero-crossing rate
plt.figure(figsize=(15, 5))
plt.semilogy(zero_crossings.T, label='Zero-Crossing Rate') plt.ylabel('Zero-Crossing Rate')
plt.xticks([])
plt.xlim([0, zero_crossings.shape[-1]]) plt.title('Zero-Crossing Rate') plt.show() import librosa
import matplotlib.pyplot as plt # Load the audio file audio_data, sr = librosa.load(audio_fp) #
Trim silence
audio_data, _ = librosa.effects.trim(audio_data) # Compute RMS energy
rms = librosa.feature.rms(y=audio_data) # Plot RMS energy plt.figure(figsize=(15, 5))
plt.semilogy(rms.T, label='RMS Energy') plt.ylabel('RMS Energy')
plt.xticks([])
plt.xlim([0, rms.shape[-1]])
plt.title('Root Mean Square (RMS) Energy') plt.show() import
librosa
import matplotlib.pyplot as plt # Load the audio file audio_data, sr
= librosa.load(audio_fp) # Trim silence
audio_data, _ = librosa.effects.trim(audio_data) # Compute spectral centroid
spectral_centroid = librosa.feature.spectral_centroid(y=audio_data, sr=sr) # Plot spectral centroid
plt.figure(figsize=(15, 5))  plt.semilogy(spectral_centroid.T, label='Spectral Centroid')
plt.ylabel('Spectral Centroid (Hz)')
plt.xticks([])
plt.xlim([0, spectral_centroid.shape[-1]]) plt.title('Spectral Centroid') plt.show() import librosa
```

```
import matplotlib.pyplot as plt # Load the audio file
audio_data, sr = librosa.load(audio_fp) # Trim silence
audio_data, _ = librosa.effects.trim(audio_data) #
Compute spectral bandwidth
spectral_bandwidth = librosa.feature.spectral_bandwidth(y=audio
_data, sr=sr) # Plot spectral bandwidth plt.figure(figsize=(15, 5))
plt.semilogy(spectral_bandwidth.T, label='Spectral Bandwidth') plt.ylabel('Spectral
Bandwidth (Hz)')
plt.xticks([])
plt.xlim([0, spectral_bandwidth.shape[-1]]) plt.title('Spectral Bandwidth') plt.show()
### SIMPLE RNN ARCHITECTURE
import numpy as np import os import
librosa import pandas as pd
from sklearn.preprocessing import LabelEncoder from tensorflow.keras.utils import
to_categorical from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense, Dropout def
extract_features(file_path):
audio, sample_rate = librosa.load(file_path, res_type='kaiser_fast') mfccs
librosa.feature.mfcc(y=audio, sr=sample_rate, n_mfcc=40) mfccs_processed
np.mean(mfccs.T, axis=0)
return mfccs_processed def load_data(data_path):
features = [] labels = []
for folder in os.listdir(data_path): if folder.startswith('.'):
continue class_label = folder
class_dir = os.path.join(data_path, class_label) for file in os.listdir(class_dir): if
file.endswith('.wav'):
file_path = os.path.join(class_dir, file) data = extract_features(file_path) features.append(data)
labels.append(class_label)
features = np.array(features) labels = np.array(labels) return features, labels #
Encode the labels le = LabelEncoder()
```

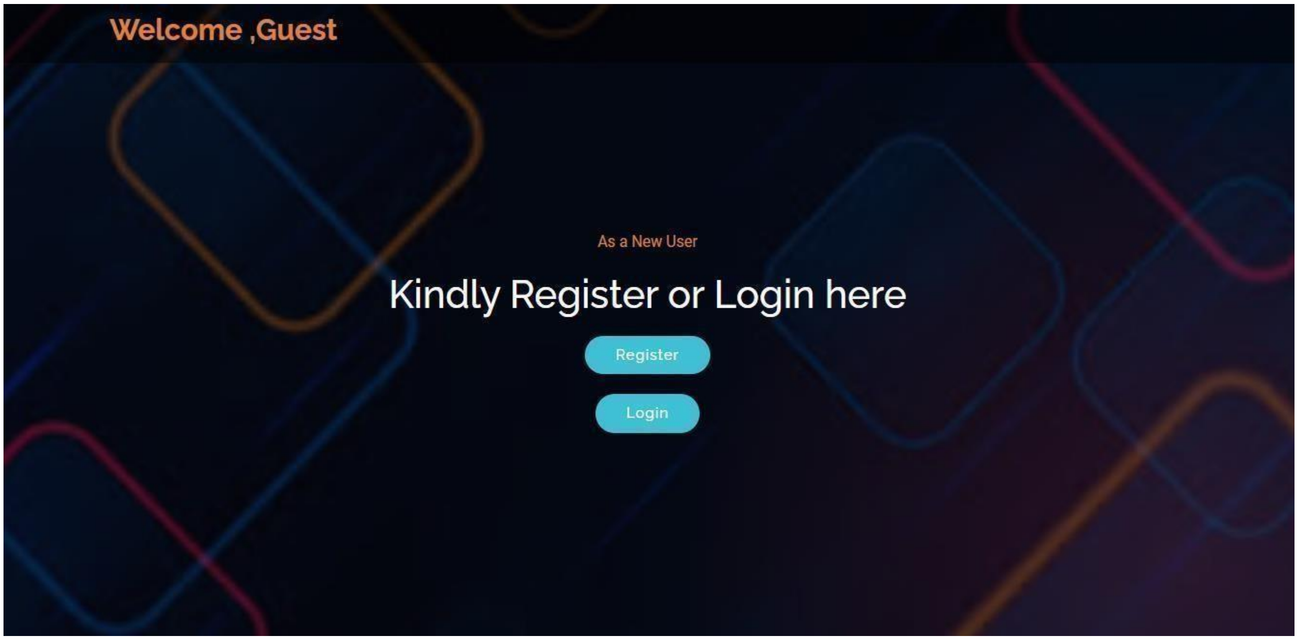
```
y_encoded = to_categorical(le.fit_transform(y)) # Reshape X for the RNN model
X_reshaped = X.reshape(X.shape[0], X.shape[1], 1) # Build the SimpleRNN model
model_rnn = Sequential()
model_rnn.add(SimpleRNN(128, input_shape=(X_reshaped.shape[1], 1),
return_sequences=True))
model_rnn.add(Dropout(0.3)) model_rnn.add(SimpleRNN(128))
model_rnn.add(Dropout(0.3))
model_rnn.add(Dense(y_encoded.shape[1], activation='softmax'))
model_rnn.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model_rnn.summary()
# Train the SimpleRNN model
history_rnn = model_rnn.fit(X_reshaped, y_encoded, epochs=50, batch_size=32,
validation_split=0.2)
# Save the SimpleRNN model
# model_rnn.save('audio_classification_model_rnn.h5') import
matplotlib.pyplot as plt
def plot_history(history, title):
plt.figure(figsize=(12, 4)) # Plot accuracy plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy') plt.title(f'{title} -
Accuracy')
plt.xlabel('Epochs') plt.ylabel('Accuracy') plt.legend()
# Plot loss plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss') plt.plot(history.history['val_loss'], label='Validation
Loss') plt.title(f'{title} –Loss')
plt.xlabel('Epochs') plt.ylabel('Loss') plt.legend() plt.show()
# Visualize SimpleRNN model training history plot_history(history_rnn, 'SimpleRNN') #
**LSTM**
## Importing the required modules
import numpy as np import os import librosa
```

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout def extract_features(file_path):
audio, sample_rate = librosa.load(file_path, res_type='kaiser_fast') mfccs =
librosa.feature.mfcc(y=audio, sr=sample_rate, n_mfcc=40) mfccs_processed = np.mean(mfccs.T,
axis=0)
return mfccs_processed def load_data(data_path): features= [] labels = []
for folder in os.listdir(data_path): if folder.startswith('.'):
continue class_label = folder
class_dir = os.path.join(data_path, class_label) for file in os.listdir(class_dir): if
file.endswith('.wav'):
file_path = os.path.join(class_dir, file) data = extract_features(file_path) features.append(data)
labels.append(class_label)
features = np.array(features) labels = np.array(labels) return features, labels #
Encode the labels le = LabelEncoder()
y_encoded = to_categorical(le.fit_transform(y)) # Build the LSTM model model =
Sequential()
model.add(LSTM(128, input_shape=(X.shape[1], 1), return_sequences=True))
model.add(Dropout(0.3))
model.add(LSTM(128))
model.add(Dropout(0.3)) model.add(Dense(y_encoded.shape[1], activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
# Reshape the data for LSTM
X_reshaped = np.expand_dims(X, axis=-1) # Train the model
history = model.fit(X_reshaped, y_encoded, epochs=200, batch_size=24, validation_split=0.2)
# Save the model model.save('audio_classification_model.h5') import matplotlib.pyplot as plt
def plot_history(history, title): plt.figure(figsize=(12, 4)) # Plot accuracy plt.subplot(1, 2, 1)
```

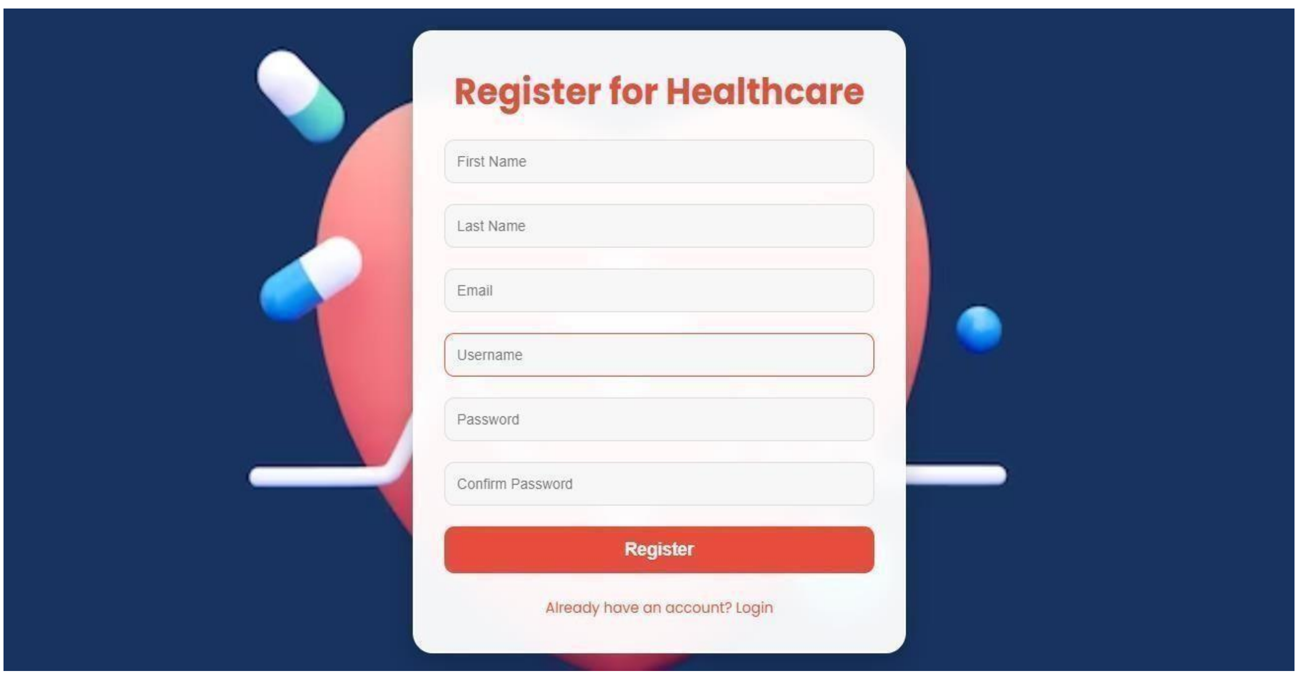
```
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy') plt.title(f'{title} -
Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy') plt.legend() # Plot
loss plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss') plt.plot(history.history['val_loss'], label='Validation
Loss') plt.title(f'{title} - Loss')
plt.xlabel('Epochs') plt.ylabel('Loss') plt.legend() plt.show()
# Visualize SimpleRNN model training history plot_history(history, 'LSTM') import
numpy as np import os
import librosa import pandas as pd import
matplotlib.pyplot as plt
from sklearn.preprocessing import
LabelEncoder from tensorflow.keras.utils
import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GRU, Dropout def extract_features(file_path):
audio, sample_rate = librosa.load(file_path, res_type='kaiser_fast') mfccs =
librosa.feature.mfcc(y=audio, sr=sample_rate, n_mfcc=40) mfccs_processed = np.mean(mfccs.T,
axis=0)
return mfccs_processed def load_data(data_path):
features = [] labels = []
for folder in os.listdir(data_path): if folder.startswith('.'): continue
class_label = folder
class_dir = os.path.join(data_path, class_label) for file in os.listdir(class_dir): if
file.endswith('.wav'):
file_path = os.path.join(class_dir, file) data = extract_features(file_path) features.append(data)
labels.append(class_label) features = np.array(features) labels = np.array(labels) return
features, labels # Example usage
```

```
data_path = 'DATASET/TRAIN/' X, y = load_data(data_path)
# Encode the labels le = LabelEncoder()
y_encoded = to_categorical(le.fit_transform(y)) # Build the GRU model model =
Sequential()
model.add(GRU(128, input_shape=(X.shape[1], 1), return_sequences=True))
model.add(Dropout(0.3))
model.add(GRU(128)) model.add(Dropout(0.3)) model.add(Dense(y_encoded.shape[1],
activation='softmax')) model.compile(loss='categorical_crossentropy', optimizer='adam',
metrics=['accuracy']) model.summary()
# Reshape the data for GRU
X_reshaped = np.expand_dims(X, axis=-1) # Train the model
history = model.fit(X_reshaped, y_encoded, epochs=50, batch_size=24, validation_split=0.2)
# Save the model model.save('gru_audio_classification_model.h5') def plot_history(history,
title):
plt.figure(figsize=(12, 4)) # Plot accuracy plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy') plt.title(f'{title} -
Accuracy')
plt.xlabel('Epochs') plt.ylabel('Accuracy') plt.legend() # Plot loss plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss') plt.title(f'{title} - Loss') plt.xlabel('Epochs')
plt.ylabel('Loss') plt.legend() plt.show()
plot_history(history, 'GRU')
```

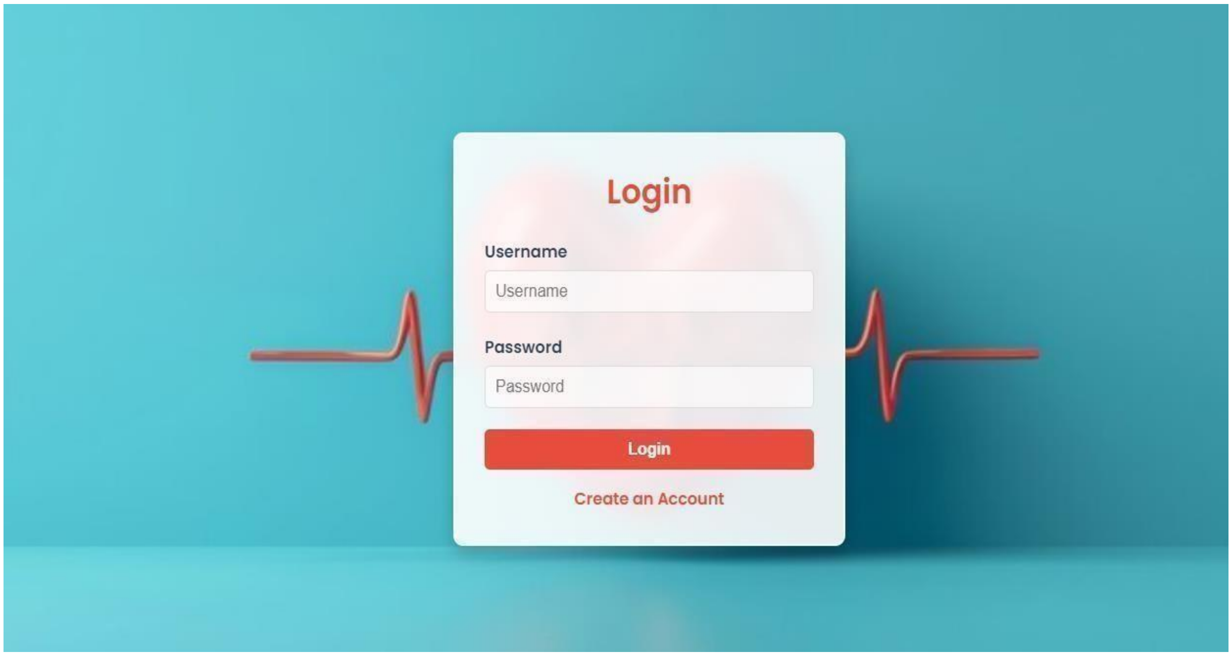
A.3 SCREENSHOTS



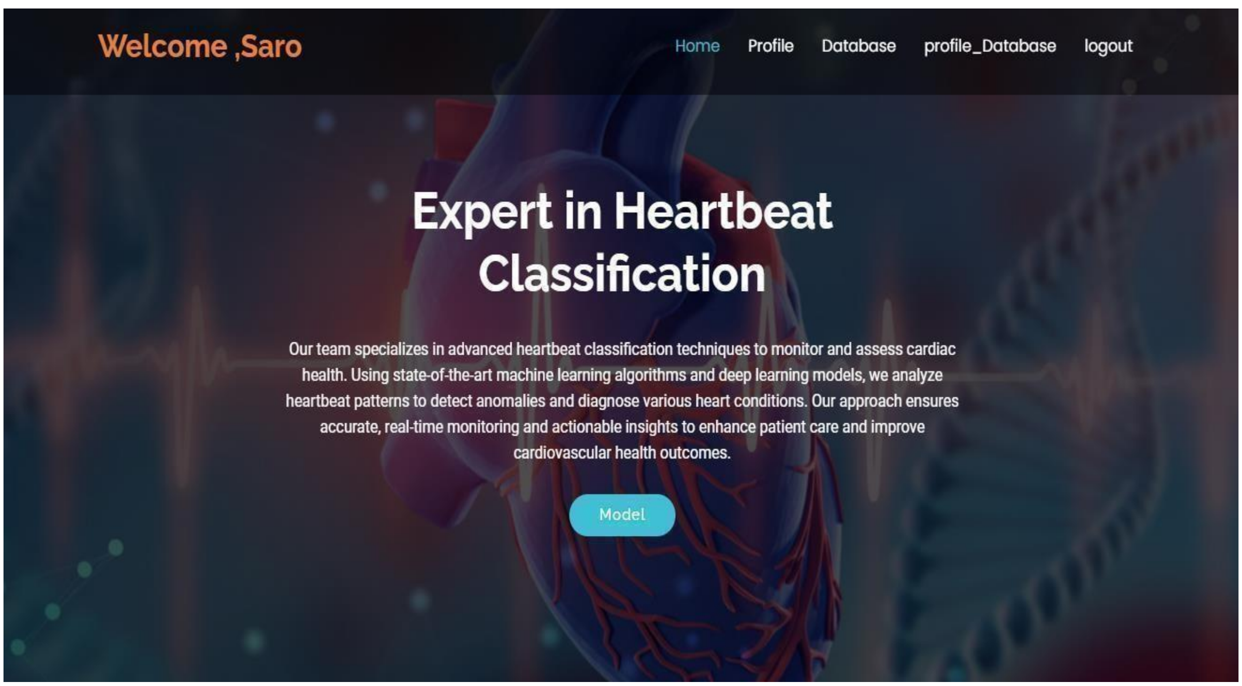
A.1 Welcome Page



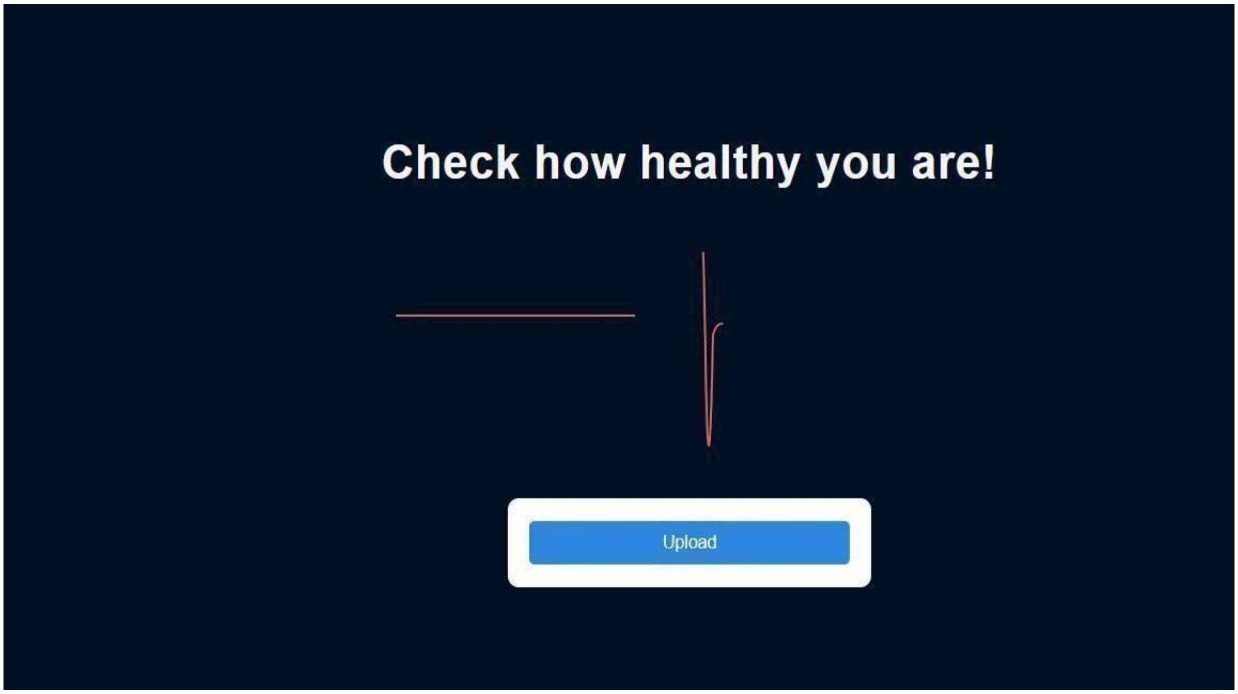
A.2 Registration Page



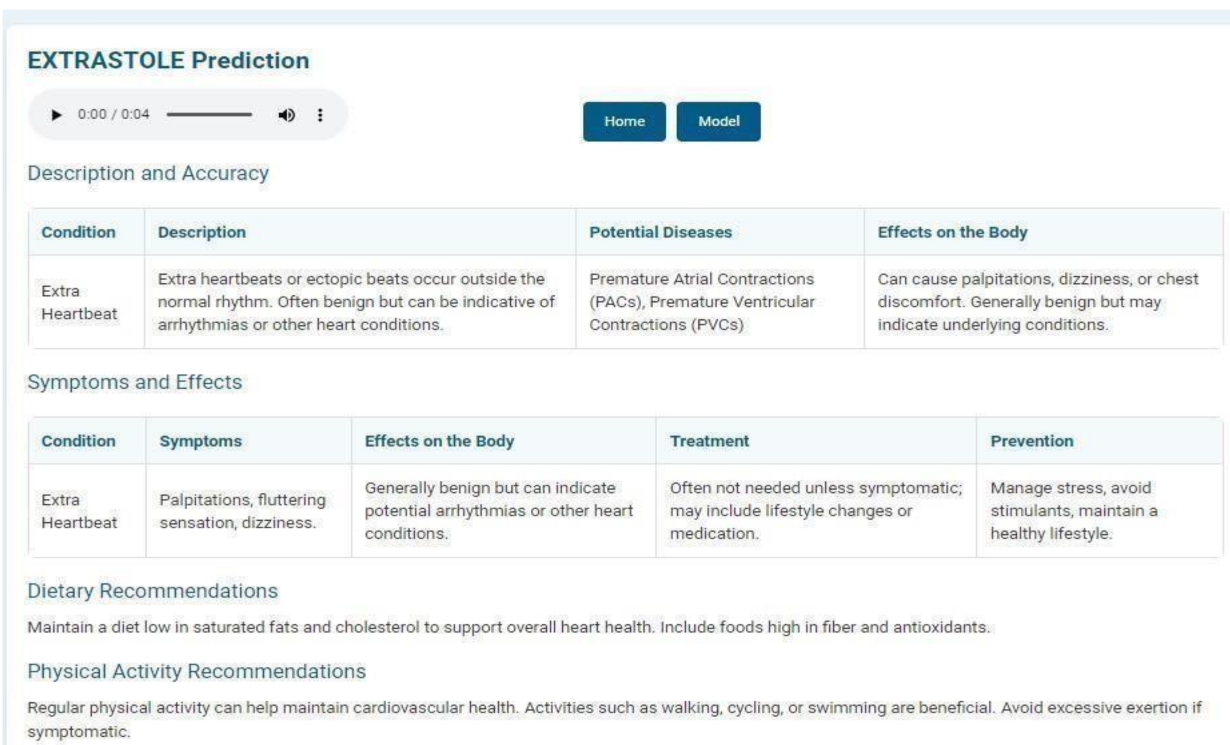
A.3 Login Page



A.4 Home Page



A.5 Audio Upload Page



EXTRASTOLE Prediction

0:00 / 0:04

Home Model

Description and Accuracy

Condition	Description	Potential Diseases	Effects on the Body
Extra Heartbeat	Extra heartbeats or ectopic beats occur outside the normal rhythm. Often benign but can be indicative of arrhythmias or other heart conditions.	Premature Atrial Contractions (PACs), Premature Ventricular Contractions (PVCs)	Can cause palpitations, dizziness, or chest discomfort. Generally benign but may indicate underlying conditions.

Symptoms and Effects

Condition	Symptoms	Effects on the Body	Treatment	Prevention
Extra Heartbeat	Palpitations, fluttering sensation, dizziness.	Generally benign but can indicate potential arrhythmias or other heart conditions.	Often not needed unless symptomatic; may include lifestyle changes or medication.	Manage stress, avoid stimulants, maintain a healthy lifestyle.

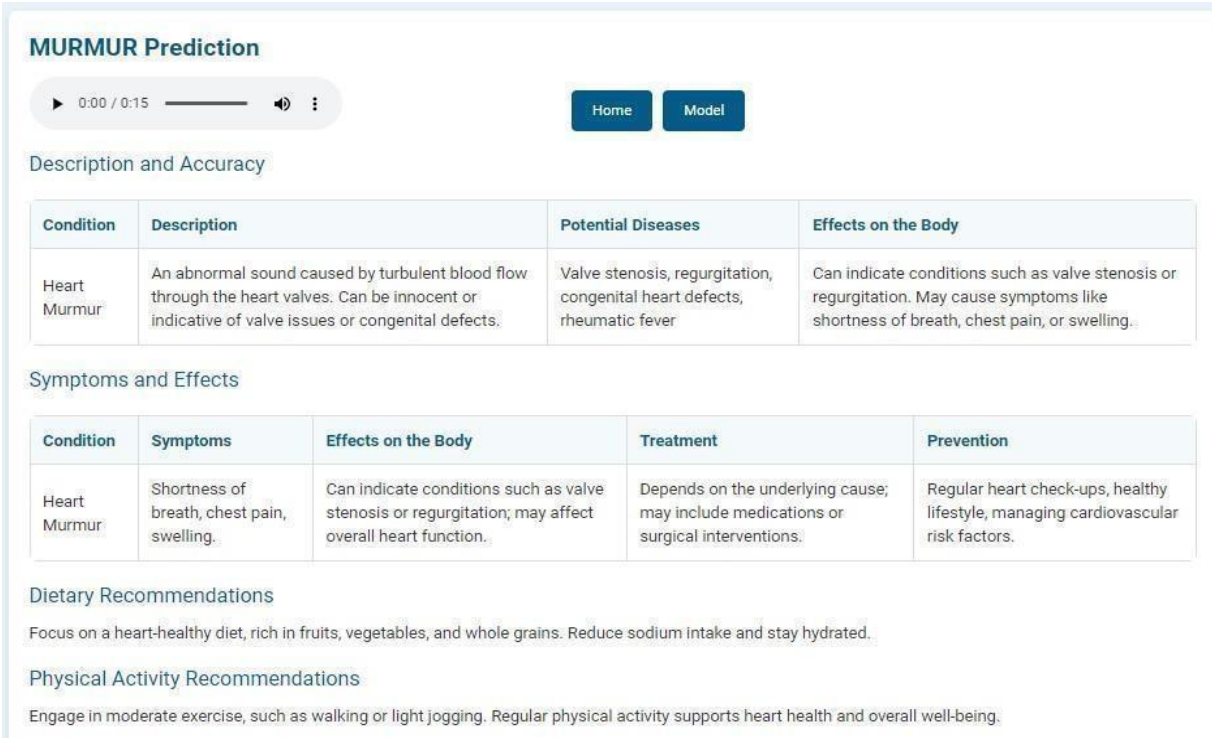
Dietary Recommendations

Maintain a diet low in saturated fats and cholesterol to support overall heart health. Include foods high in fiber and antioxidants.

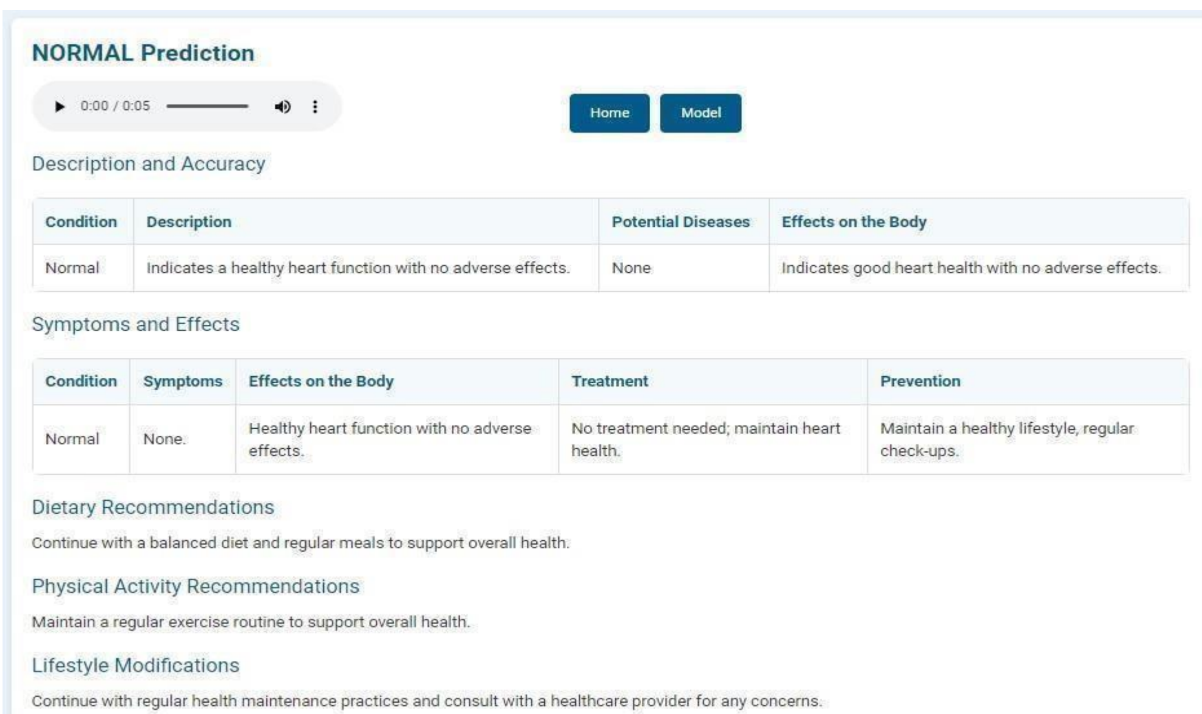
Physical Activity Recommendations

Regular physical activity can help maintain cardiovascular health. Activities such as walking, cycling, or swimming are beneficial. Avoid excessive exertion if symptomatic.

A.6 Output Screenshot-1



A.7 Output Screenshot-2



A.8 Output Screenshot-3

A.4 PLAGIARISM REPORT

Likitha Ravichandran

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Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis

***Abstract*— This research presents an innovative method for analyzing heart sounds by integrating machine learning models into an accessible web application created with the Django framework. In order to identify and diagnose various heart illnesses early on, The main objective is to establish a trustworthy and efficient system for classifying cardiac sounds from audio recordings. The system provides thorough medical information, including linked illnesses, their causes, preventative measures, etc., after analyzing and classifying heart sound recordings into several groups. The Django framework is a powerful backend solution that ensures secure data management and smooth user interaction. The ability of the system to store and retrieve historical data from a centralized database makes it a valuable tool for clinicians to monitor and assess heart health. By combining machine learning with a scalable internet application, the initiative aims to encourage the broader usage of automated heart sound analysis, which will ultimately improve patient outcomes and medical procedures.**

***Keywords*— Accuracy, comparison, RNN, LSTM, GRU, Web integration, Django.**

I. Introduction

New applications in the healthcare sector have been made possible by developments in machine learning and artificial intelligence. A vital aspect essential for the early identification and diagnosis of cardiovascular diseases is the analysis of heart sounds. This article introduces a clever approach that uses recurrent neural networks (RNN) to effectively classify recordings of heart sounds. When included into a web-based platform developed using the Django framework, the system provides a practical and easy-to-use method for analyzing heart sounds. The proposed method not only automates the classification process but also provides extensive medical insights, including linked diseases, causes, and preventive actions. The goal of combining state-of-the-art technology with clinical applications is to increase diagnostic precision and optimize productivity in medical settings.

A. Objectives

The primary aim of this project is to develop a reliable and efficient classification system utilizing machine learning techniques for the analysis of heart sounds. The specific objectives are as follows:

Automated Classification: To aid in the early identification of cardiac disorders, classify heart sound recordings into different groups using machine learning algorithms.

User-Friendly Web Application: Use the Django framework to build an interactive, scalable web platform that ensures accessibility and smooth user interaction.

Medical Advice and Insights: Provide thorough medical advice that covers associated ailments, potential causes, and preventative measures to assist medical professionals in making judgments.

Data Management and Storage: To enable continuous patient monitoring, establish a centralized database to securely store and retrieve previous cardiac sound recordings.

Clinical Utility and Integration: To assist medical professionals in more accurately diagnosing and treating cardiovascular illnesses, make the system simpler to utilize in clinical settings.

The program aims to help with the early detection and prevention of heart problems in order to enhance patient outcomes and healthcare practices.

B. Literature Review

Deep learning algorithms have shown enhanced effectiveness in analyzing intricate cardiac sound patterns, surpassing the results obtained from traditional machine learning methods such as K-Nearest Neighbors (KNN) and Support Vector Machines (SVM). Additionally, research has focused on explainability techniques to ensure that model predictions are understandable, thereby assisting healthcare professionals in their decision-making processes. This effort aims to build on these findings by developing a scalable and efficient heart sound analysis system that links research with practical clinical application.

TABLE I. INFERENCES FROM LITERATURE REVIEW

S. No	Source	Methodology	Inference
1.	Ren Z. et al. [1]	This research offers an extensive examination of applied cardiac sounds.	Highlights gaps in real-time applications suggests future research directions in automated analysis.
2.	Mohan S. et al. [2]	The research combines multiple machine learning models to predict heart disease effect	Demonstrates potential with improved accuracy but lacks validation on robust real-world datasets.
3.	Alrabie S. et al. [3]	The study introduces a multiclass dataset and applies CNN for cardio vascular disease detection.	Introduces a multiclass dataset, effective for disease detection but with limited data for certain diseases.
4.	Hamza M. F. A. B. et al. [4]	This survey provides an overview of deep learning and machine learning techniques utilized for the analysis of cardiac sounds.	Surveys techniques, challenges, and advancements but lacks specific deep model implementations.
5.	Qiao L. et al. [5]	This technique uses a dynamic mask encoder in conjunction with time-compressed and frequency-expanded TDNN to identify irregularities in cardiac sounds.	Combines embeddings and time- frequency features for high accuracy but requires preprocessing steps.
6.	Fernando T. et al. [6]	The research employs bidirectional LSTMs with an attention mechanism for segmenting heart sounds.	Improves segmentation accuracy, leveraging attention mechanisms, but is computationally expensive.
7.	Zhang H. et al. [7]	A decision fusion network combining multiple features and decision-making processes is used for detection.	Combines multiple features for robust detection, requiring high computational resources.
8.	Susic D. et al. [8]	The study introduces PCGmix, a novel data augmentation technique, to improve heart sound classification.	Boosts accuracy and generalization but may not cover all real-world scenarios.
9.	Katarya R. et al. [9]	This survey examines different machine learning techniques aimed at the early prediction of heart disease.	Offers an assessment of machine learning; however, it does not include experimental validation tailored to heart sounds.
10.	Chen J. et al. [10]	Ensemble learning methods are employed by combining multiple classifiers for heart sound classification.	Achieves high accuracy by combining classifiers but can be computationally intensive.
11.	S. V. R. et al. [11]	The research employs wavelet packet transform for the extraction of features and utilizes machine learning techniques for classification purposes.	Combines signal processing with ML for improved detection but needs more real-world validation.
12.	Lee J. et al. [12]	The research applies deep learning techniques frequency-time domain features for heart murmur detection.	Effective at murmur detection but tested on a limited dataset.
13.	Habijan M. et al. [13]	Deep learning models are utilized for accurate heart sound classification.	Achieves high accuracy but faces data imbalance challenges.
14.	Roy T. S. et al. [14]	The study uses a CNN-based residual network to predict valvular heart disease.	Improves prediction for valvular diseases but requires large datasets for training.
15.	Banerjee M. et al. [15]	A 2D convolutional neural network is applied for multi- class classification of heart sounds.	Allows high-accuracy multi-class classification but may not generalize across populations.
16.	Qiao P. et al. [16]	Wavelet analysis is combined with random forest algorithms to diagnose adolescent heart sounds.	Targets adolescent heart sound diagnosis, with limited generalization to other age groups.
17.	Bao X. et al. [17]	The study compares time-frequency distribution techniques for enhancing CNN's ability to classify cardiac sounds.	Optimizes CNNs for heart sounds but explores limited TFD techniques.
18.	Grooby E. et al. [18]	Signal quality assessment methods are combined withmachine learning to estimate heart and lung rates in neonates.	Focuses on neonatal sound quality for telehealth, limited to specific applications.
19.	Tsai K.-H. et al. [19]	A self-supervised model is utilized to separate lung and heart sounds using a deep autoencoder that is periodic-coded.	Innovative unsupervised separation model but computationally expensive.

II. REASEARCH METHODOLOGY

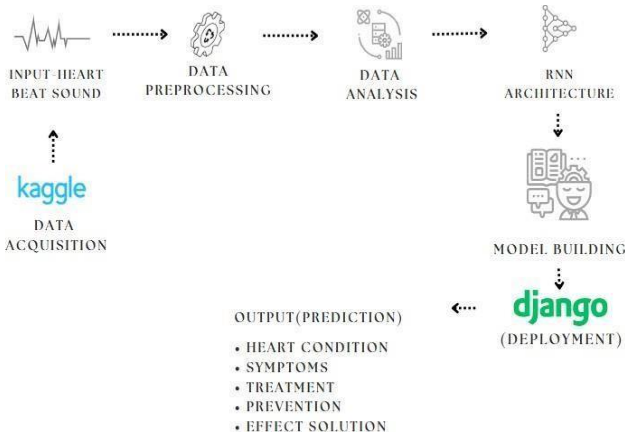

Fig.1 ARCHITECTURE DIAGRAM OF THE APPROACH

This architecture diagram shows the entire process of machine learning-based heart sound analysis, from data collection to deployment. First, heartbeat sound data is gathered, either from publicly accessible datasets like Kaggle or from medical equipment. To remove noise, normalize signals, segment audio, and extract crucial parameters like frequency or Mel-Frequency Cepstral Coefficients (MFCCs), the raw data is first preprocessed. After that, any data imbalances are addressed and patterns are found using exploratory data analysis. The system's central component is an RNN (Recurrent Neural Network) architecture, which has been shown to perform more accurately for this particular application than Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. To efficiently classify heart sounds and forecast possible cardiac problems, the RNN is trained on preprocessed data. The model produces outputs including cardiac disease forecasts, preventive actions, suggested precautions, and customized remedies for situations that have been recognized after training is finished. After the training phase, the model is integrated into a Django web application, allowing users to upload heart sound recordings, receive real-time predictions, and obtain actionable insights through a user-friendly interface. This thorough process leverages machine learning to support the early detection and diagnosis of cardiac conditions.

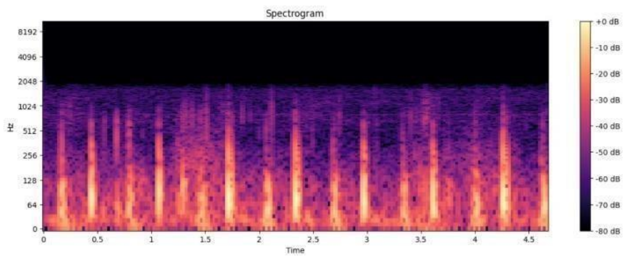

Fig. 2 SPECTOGRAM GRAPH FOR FEATURE EXTRACTION

The spectrogram illustrates the time-frequency distribution of heart sound data, with frequency (measured in Hertz) represented on the y-axis and time (in seconds) on the x-axis. Brighter sections imply that the majority of energy is focused below 512 Hz. Brighter regions are associated with particular heartbeats or occurrences, and the color intensity represents energy levels. The algorithm finds patterns for precise heart sound categorization with the help of this visualization, which facilitates feature extraction

III. EXPERIEMENTAL RESULT ANALYSIS

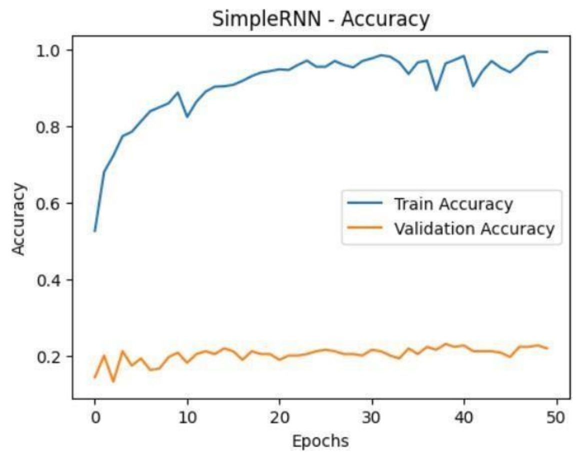

Fig.3 SUB PLOT OF SIMPLE RNN-ACCURACY

This graph illustrates the SimpleRNN model's robust learning ability. The model shows a steady and significant improvement in training accuracy as training goes on, eventually performing almost flawlessly on the training set. This demonstrates how well the model can identify and understand the patterns in the training dataset.

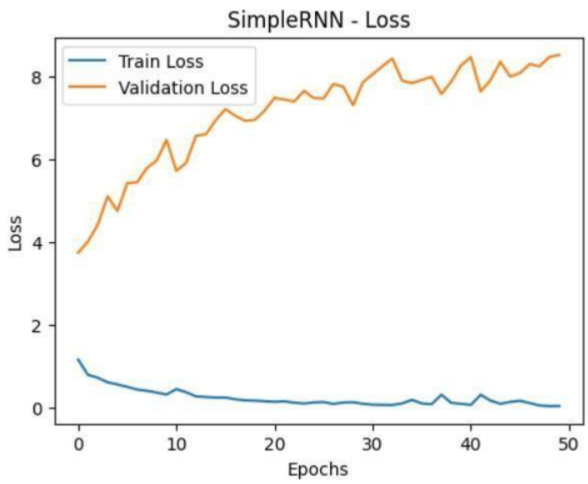

Fig.4 SUB PLOT OF SIMPLE RNN-LOSS

This figure demonstrates that training loss is effectively reduced by the SimpleRNN model. The consistent and noticeable reduction in training loss with the ages shows how well the model can learn and match the training data. This illustrates the models performance and Capacity to improve prediction accuracy on the training set.

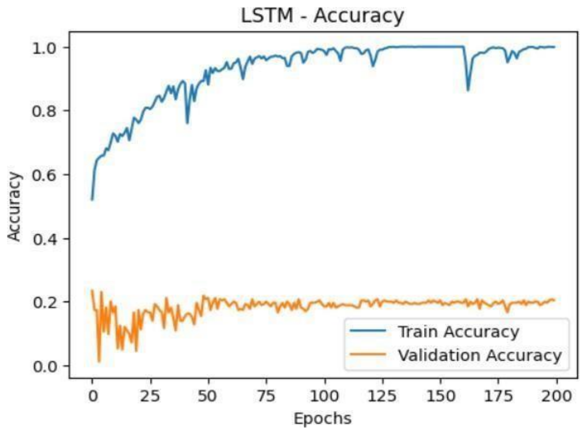

Fig.5 SUB PLOT OF LSTM-ACCURACY

This graph illustrates the LSTM model's remarkable learning efficiency. The incredibly high accuracy the model achieves on the training data in a short amount of training epochs demonstrates its amazing capacity to quickly identify and understand complex patterns. This ability to learn quickly demonstrates how effectively LSTM models can process intricate sequential input.

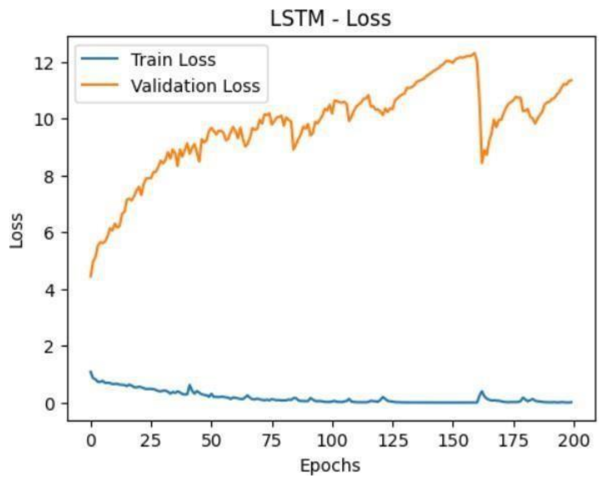

Fig.6 SUB PLOT OF LSTM-LOSS

This graph showcases the remarkable capability of the LSTM model to enhanceits performance on the training set. The consistent and efficient decrease in training loss indicates the model's proficiency in learning and adjusting to thintricacies of the training dataset. The model's effective training loss optimization demonstrates its capacity to produce precise predictions.

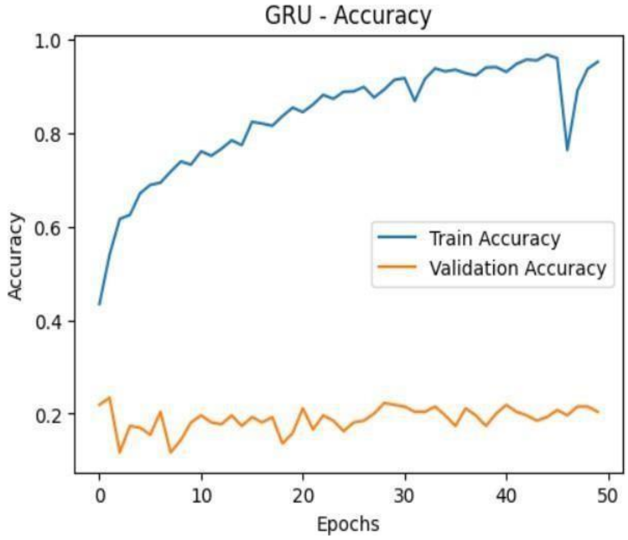

Fig.7 SUB PLOT OF GRU-ACCURACY

This graph shows how well the GRU model learned from thetraining data. The model performs well and shows a discernible and consistent improvement in training accuracy. Its ability to identify and assimilate patterns in the training dataset is demonstrated by this.

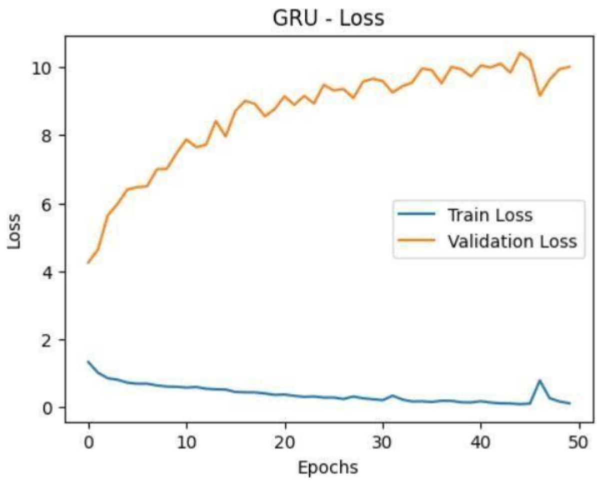

Fig.8 SUB PLOT OF GRU-LOSS

Given that the validation loss thus declines in the early epochs, the model exhibits strong initial generalization ability. This indicates that both the hyperparameters and the model architecture are fundamentally effective and capable of retrieving relevant information from the data. All things considered, the downward trend in losses, particularly during the first phase, is encouraging and shows that the model may function effectively with the right modifications.

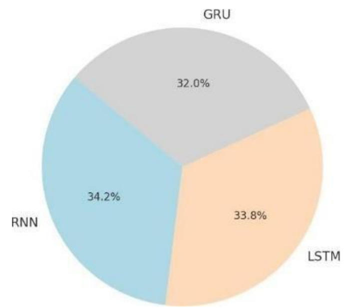

Fig.9 PIE CHART OF THE COMPARISON

3 The percentage of real positive cases that each model accurately identified is shown in this pie chart. 94% of the true positive cases are successfully identified by the RNN model, which has a 94% recall. With a 93% recall, the LSTM model comes in second, and the GRU model has an 88% recall. This suggests that RNN outperforms both LSTM and GRU in detecting positive cases from the dataset. In terms of accuracy, recall, and precision, RNN routinely beats LSTM and GRU, according to these comparison criteria, which makes it a good model for heart sound analysis.

8 *TABLE II. ACCURACY ANALYSIS OF THE ALGORITHMS*

10

Classifier	Accuracy
RNN	94. 0
LSTM	93. 0
GRU	88. 0

IV. Conclusion

In this study, we used the Librosa package to evaluate the LSTM and RNN architectures for heartbeat sound analysis. RNN was chosen for our implementation because of its increased efficiency. The model illustrated deep learning's potential in biomedical signal processing by successfully classifying different pulse types based on extracted acoustic parameters. The smooth interface that allowed users to upload audio files and get real-time predictions thanks to integration with Django highlighted the usefulness of this study in clinical settings. Even with the effectiveness of the suggested system, there is still room for improvement in areas like imbalance in the data, processing in real time, and interpretability of the model. Studies in the future might concentrate on adding real-time monitoring capabilities, diversifying datasets, and integrating explainable AI approaches. All things considered, this effort advances automated heart sound analysis, opening the door to more effective, precise, and easily available cardiac diagnosis tools. The integration of machine learning in healthcare holds significant promise for improving clinical workflows and patient outcomes.

V. Discussion

RNN, LSTM, and GRU were among the deep learning architectures that were compared in order to determine which was besuited for this task. Although LSTM and GRU are well- known for managing long-term dependencies, RNN demonstrated superior accuracy at a lower computational cost. The findings show that because deep learning-based methods can recognize intricate patterns, they perform noticeably better in heartbeat classification than conventional machine learning techniques. Additionally, a user-friendly online interface made possible by the Django connection allowed for real-time forecasts and smooth audio file submissions. This valuable application enhances access to advanced cardiac testing, potentially serving as a significant tool for the early identification of heart disease. Notwithstanding its achievements, the system's functionality could be enhanced even more by investigating cutting-edge architectures such as transformer-based models, optimizing hyperparameters, and adding more varied datasets.

VI. .FUTURE ENHANCEMENTS

Model Optimization: Through the exploration of intricate architectures such as hybrid models, which integrate Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs), the machine learning models (including RNN, LSTM, and GRU) can be enhanced to boost accuracy and minimize both false positives and false negatives in the classification of heart sounds.

Real- Time Analysis: Put in place real-time heart sound recording and analysis so that users can record and get prompt heart health feedback. This would improve the system's usefulness in clinical settings and user experience.

Extend Dataset: To increase the model's generalizability, incorporate a larger and more diversified collection of heart sound recordings, such as those from individuals with a range of medical problems, age groups, and ethnicities.

Multi-Modal Integration: For a more thorough diagnosis, combine information from additional diagnostic instruments, such as X-rays or ECGs. This may provide a more comprehensive understanding of the patient's heart condition and enhance the accuracy of predictions.

User Personalization: Include tools that allow users to customize the app according to their medical history. For example, make recommendations for particular cardiac diseases or offer insights based on historical health patterns.

Integration of Mobile Applications: Create a smartphone app that will make it simple for people to capture heart sounds and get immediate analysis, increasing accessibility.

Explainable AI: Include explainability elements that assist users in comprehending the rationale behind particular classifications or forecasts. Particularly in clinical contexts, this could contribute to the development of systemic trust
.

Long-Term Monitoring and Alerts: Provide patients with chronic illnesses with long-term cardiac sound monitoring. When abnormalities are found, alert medical experts, enabling improved continuing treatment.

Global Language Support: Add multilingual support to accommodate users from around the world, extending the tool's reach and making it usable for non-native English speakers.

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A.5 PAPER PUBLICATION

ADHIPARASAKTHI COLLEGE OF ENGINEERING

#880 (1571131070): *Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis*

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Paper title	*Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis*
Conference and track	2025 11th International Conference on Communication and Signal Processing (ICCSP) - *AI-Driven Data Analysis: Deep Learning for Pattern Recognition and Predictive Modeling*
Abstract	This research presents an innovative method for analyzing heart sounds by integrating machine...
Keywords	Accuracy; comparison; RNN,LSTM,GRU; Web Integration; Django
Conference-specific	*I have added all co-authors in EDAS as in the manuscript:* ✅
Personal notes	
Non-preferred reviewers	
Roles	You are the creator and an author for this paper.
Status	Active (has manuscript)

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Submission Summary Conference Name

International Conference on Computer, Communication and Signal Processing 2025

Paper ID

358

Paper Title

Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis

Abstract

This research presents an innovative method for analyzing heart sounds by integrating machine learning models into an accessible web application created with the Django framework. In order to identify and diagnose various heart illnesses early on, The main objective is to establish a trustworthy and efficient system for classifying cardiac sounds from audio recordings. The system provides thorough medical information, including linked illnesses, their causes, preventative measures, etc., after analyzing and classifying heart sound recordings into several groups. The Django framework is a powerful backend solution that ensures secure data management and smooth user interaction. The ability of the system to store and retrieve historical data from a centralized database makes it a valuable tool for clinicians to monitor and assess heart health. By combining machine learning with a scalable internet application, the initiative aims to encourage the broader usage of automated heart sound analysis, which will ultimately improve patient outcomes and medical procedures.

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Name

2025 2nd International Conference on Computing and Data Science (ICCDS)

Paper ID - 207

Paper Title

Transforming Cardiac Diagnostics with Machine Learning Powered Cardio Acoustic Analysis

Abstract

This research presents an innovative method for analyzing heart sounds by integrating machine learning models into an accessible web application created with the Django framework. In order to identify and diagnose various heart illnesses early on, The main objective is to establish a trustworthy and efficient system for classifying cardiac sounds from audio recordings. The system provides thorough medical information, including linked illnesses, their causes, preventative measures, etc., after analyzing and classifying heart sound recordings into several groups. The Django framework is a powerful backend solution that ensures secure data management and smooth user interaction. The ability of the system to store and retrieve historical data from a centralized database makes it a valuable tool for clinicians to monitor and assess heart health. By combining machine learning with a scalable internet application, the initiative aims to encourage the broader usage of automated heart sound analysis, which will ultimately improve patient outcomes and medical procedures.

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