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Rnn-Based Heartbeat Sound Analysis with Django Integration

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Abstract- This research work presents an innovative approach to heartbeat audio classification using Recurrent Neural Networks (RNNs) integrated with the Django framework. The primary aim is to develop an efficient and accurate system for classifying heartbeat sounds to aid in the early detection and diagnosis of cardiac conditions. The system leverages RNNs, which are particularly suited for processing sequential data, to analyze and classify heartbeat audio recordings. The Django framework facilitates seamless integration, providing a robust and scalable web application for data management, model deployment, prediction. The RNN model is trained on a diverse dataset of heartbeat audio recordings, enabling it to recognize various cardiac anomalies. The proposed system demonstrates high accuracy and reliability, making it a valuable tool for healthcare professionals. Additionally, the integration with Django ensures that the system can be easily accessed and utilized in clinical settings, promoting widespread adoption and improving patient outcomes.

Keywords- Recurrent Neural Networks (RNNs), heartbeat audio classification, Django integration, cardiac conditions, sequential data processing, model deployment, patient outcomes.

I. INTRODUCTION

In recent years, the analysis of heartbeat sounds has garnered significant attention in the field of medical diagnostics, particularly due to its potential to detect cardiovascular abnormalities early. Utilizing advanced machine learning techniques, especially Recurrent Neural Networks (RNNs), offers a powerful approach to processing and interpreting the intricate patterns inherent in heartbeat audio signals. This project focuses on employing librosa, a robust library for audio analysis in Python, to extract meaningful features from heartbeat sounds. By integrating SimpleRNN and Long Short-Term Memory (LSTM) networks, we can harness the sequential nature of heartbeat data, allowing the model to learn from temporal dependencies and capture subtle variations that may indicate underlying health issues. The incorporation of Django for web application development facilitates a user-friendly interface, enabling healthcare professionals and researchers to easily upload and analyze audio recordings of heartbeat sounds. This holistic approach not only aims to improve diagnostic accuracy but also seeks to democratize access to advanced cardiovascular analysis tools, potentially leading to better patient outcomes through timely intervention. The convergence of audio analysis, deep learning, and web technology positions this project at the forefront of innovative solutions in healthcare, making it an essential contribution to the ongoing evolution of digital health diagnostics.

Heartbeat sound analysis plays a critical role in the early detection of cardiovascular diseases, offering a non-invasive and cost-effective diagnostic tool. This project presents an intelligent system that utilizes Recurrent Neural Networks (RNNs),

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specifically Long Short-Term Memory (LSTM) architectures, to classify heart sounds as normal or abnormal based on phonocardiogram (PCG) recordings. The system incorporates signal preprocessing techniques such as noise filtering, segmentation, and feature extraction using Mel-Frequency Cepstral Coefficients (MFCCs) to improve model accuracy.

To enhance usability and accessibility, the machine learning model is integrated into a web-based application using the Django framework. The platform enables users—especially healthcare professionals and researchers—to upload heartbeat audio samples, visualize spectrograms, and receive instant classification results through an intuitive graphical user interface. The backend handles preprocessing, model inference, and result interpretation in real time. Extensive testing on benchmark datasets demonstrates high classification accuracy and robustness against noise, validating the system's effectiveness for practical applications. This integration of deep learning with web technologies provides a scalable and user-friendly tool for automated cardiac screening and telemedicine solutions.

Fig 1: Heartbeat Ultrasound

Literature Survey

Przybyło, J. (2022), discuss a deep learning approach for remote heart rate monitoring using Video plethysmography (VPG). VPG allows non-contact heart rate monitoring by analyzing video data. This type of monitoring is advantageous for telemedicine and remote patient monitoring. Traditional methods for extracting VPG signals rely on complicated multistage algorithms. The paper proposes employing a Long Short-Term Memory (LSTM) Deep Neural Network to simplify and improve this process' accuracy. The LSTM-based method achieves comparable results to cutting-edge techniques such as Independent Component Analysis (ICA) and Plane Orthogonal to the Skin (POS), with error rates of 3.26 bpm, 3.02 bpm, and 2.61 bpm, respectively. Furthermore, the LSTM approach works well with infrared lighting, making it ideal for a variety of telemedicine applications, including overnight monitoring. This method lowers the requirement for preprocessing and parameter selection, providing a more efficient alternative for continuous heart rate monitoring.

This study provides a comprehensive overview of four deep learning methods for heart rate monitoring from video clips: STVEN-rPPGNet, IPPG-3D-CNN, PhysNet, and Meta-rPPG. All these methods utilize various network architectures and techniques to enhance and analyse video data for accurate heart rate estimation. PhysNet demonstrated the highest accuracy compared to the other algorithms in terms of Mean Absolute Error and Mean Square Error. UBFC database is used for training and testing, highlighting the effectiveness of deep learning approaches over conventional methods. However, limitations such as computational complexity and dataset dependency were noted. (Ni et al., 2021).

In the study of heart rate estimation, (Chang, 2019) proposes a novel approach for robust heart rate estimation using wrist-worn devices. Combining deep learning based denoising with spectrum analysis calibration, DeepHeart effectively cleans PPG signals contaminated by motion artifacts. By training a denoising convolutional neural network (DnCNN) on synchronized ECG-PPG data, it achieves superior accuracy, with an average absolute error of 1.98 bpm on a diverse dataset. Compared to existing methods like TROIKA and Deep PPG, DeepHeart demonstrates significant performance improvements, making it a promising advancement in wearable health monitoring technology.

(Patil et al., 2019) discuss the regular patient monitoring method that is uncomfortable and comparably complex procedure than the remote patient monitoring system. So, focus is to design a wireless belt that continuously monitors human pulse rate and temperature, which is used to minimize the hardware complexity and reduce the cost significantly. The proposed remote patient monitoring system uses PPG technique. PPG technique takes signal from body and sends to selected persons for monitoring, On the other hand, the notification is send using SMS facility, which is not the best method depending on limited character count, poor delivery rates, lack of context, cost and security concerns. Hence, people are also feeling uncomfortable wearing the belt every time.

(Rotariu1 et al. 2011) shows the remote blood pressure and heart rate monitoring system that is capable to measure and transmit patient's arterial blood pressure and heart rate. The proposed system is used to do long time patient monitoring as a form of PDA that runs personal heart rate monitoring application, sense and collect data and give alarms when exceed limit. Telemedicine offers medical facilities to many patients from remote locations at less time. Patient can save time, money and comfort. On the other hand, primary cause of hypertension is unknown. The proposed method is Oscillometric method that is used in the measurement of blood pressure which is compared with auscultatory (Korotkoff) method that is more precise. The Oscillometric method consumes less power and high peak performance.

(Subhan et al., 2023) The study focused on all the most trending wearable Medical Internet of Things (IoMT) for healthcare systems that make advancements. These wearable things are scrutinized from the view of efficiency in detecting, preventing, and monitoring diseases in healthcare including Covid-19 and monkey pox. These devices are the heart of IoT related health care system because it has the potential to bring major transformation. The paper makes comparison analysis between different types of IoMT things and tries to bring out the best devices possible. Hence using wearable devices can be the reason of Burning, Electric shocks, Explosion, Skin Damage, Reactions problems.

(Bathild et al., 2018) The study shows detection of atrial fibrillation by checking variations in heart rate period. This a atrial fibrillation works on light-based sensors like PPG that is non- invasive. This PPG sensor consists of a photodetector LED that collects signals from blood volume and flow. Hence, the collected signals contain a lot of noise known as motion artifacts. The proposed system's main goal is to find the successive moments of instantaneous heartbeat and measure the time between heartbeats called the Inter Beat Interval (IBI).

(Kazi et al. 2018) In a study it is mentioned that heart disease is the reason of millions of deaths. In this situation, monitoring heart is become very important. The research, focus on the real-time heart disease monitoring system, which will be done by the doctor continuously without visiting the patient physically. A developed bracelet prototype is introduced through this study that can detect multiple parameters of the body such as blood pressure, temperature, and heart rate. Arduino UNO is used to analyze the collected data and detect abnormalities. By using this technology, doctor can provide quick services remotely and cost of healthcare will be decrease. As a result, more patient can get treatment at a short period of time.

Proposed Methodology

The proposed system for Recognition RNN-Based Heartbeat Audio Classification with Django Integration leverages Recurrent Neural Network (RNN) architectures to analyze and classify heartbeat audio signals for medical diagnostics. This system collects audio recordings of heartbeats, processes them to extract relevant features, and uses a trained RNN model to classify the heartbeats into categories. The Django framework serves as the backbone for the web application, facilitating user interaction, data management, and visualization of the classification results. Users can upload audio files through the Django-based interface, receive immediate feedback on the classification, and access a comprehensive database of recorded results and associated. This integration aims to provide an efficient and accessible tool for early detection of Heartbeat conditions, improving diagnostic accuracy and patient outcomes.

To determine whether a recorded sound is associated with a healthy or sick heart, heart sound analysis is used. This research is a component of a larger effort to develop a robotic system that can acquire and analyze heart sounds called a remote auscultation system. This work only addresses the analysis because acquisition is primarily a mechanical process. Further, the work does not attempt to identify any disorders; rather, it only seeks to identify their presence. In other words, there are two categories for heart sounds: “healthy” and “diseased.” This problem is simpler compared to multi-class disease diagnosis, but it allows one method which does not include the need to segment heart sounds. This also makes the speech recognition system insensitive to difficult-to-segment sounds where the signal has been corrupted.

It is important to compare the performance of multiple different machine learning algorithms consistently and it will discover to create a test harness to compare multiple different machine learning algorithms in Python with scikit-learn. It can use this test harness as a template on your own machine learning problems and add more and different algorithms to compare. Each model will have different performance characteristics. Using resampling methods like cross validation, you can get an estimate for how accurate each model may be on unseen data. It needs to be able to use these estimates to choose one or two best models from the suite of models that you have created. When have a new dataset, it is a good idea to visualize the data using different techniques in order to look at the data from different perspectives. The same idea applies to model selection. You should use a number of different ways of looking at the estimated accuracy of your machine learning algorithms in order to choose the one or two to finalize. A way to do this is to use different visualization methods to show the average accuracy, variance and other properties of the distribution of model accuracies.

The below 2 different algorithms are compared:

- Simple RNN Architecture
- Long-Short term memory networks

Results And Discussions

The analysis two datasets taken from the Kaggle (previously PASCAL) Heart Sound Classification Contest. The first one is called A which contains actual field trials data gathered by means of using a digital stethoscope, usually containing accompanying noise like speech, traffic, or even accidental contacts with microphones when on clothes or skin. Audio file durations are about 1-30s as well. The initial step involved splitting the Pascal competitions datasets into training and test set. Dataset A had four classes (normal, murmur, Extrasystole, and echocardiography artifacts), while dataset B had three classes (normal, murmur and Extrasystole) as shown in Table 1.

Category	Normal	Murmur	Artifact	Extrasystole	Arrhythmia	Frequency (Hz)	Bit size
Dataset A(Testing)	31	34	40	19	66	44100	16
Dataset B(Training)	200	95	-	45	-	44100	16

TABLE 1: Heartbeat Datase

Heart Sound Analysis

The 4 types of heart sound and related parameters are the original heart sound is shown in figure 2: (a) Normal (b) Murmur (c) Extrasystole (d) Artifact

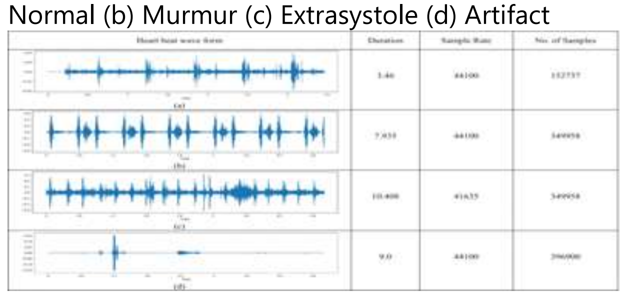

FIG 2: Types of Heartbeat

II. CONCLUSION

In this research work, we successfully implemented a RNN-based model using SimpleRNN and LSTM architectures for analyzing heartbeat sounds with the Librosa library. The model demonstrated a robust ability to classify different heartbeats based on the extracted audio features, showcasing the potential of deep learning techniques in biomedical signal processing. The integration with Django provided a seamless interface for users to upload audio files and receive real-time predictions, highlighting the practical applicability of this research in clinical settings.

To make the solution accessible and user-friendly, the trained model was integrated into a Django-based web application. This platform allows users, including medical professionals and researchers, to upload heartbeat recordings and instantly receive diagnostic feedback through an intuitive interface. The system also supports basic visualizations like waveforms and spectrograms, aiding interpretability.

Overall, the project highlights the potential of combining deep learning and web technologies to build intelligent, real-time, and scalable health diagnostic tools. It opens pathways for further enhancements, including support for multi-class classification, real-time monitoring using IoT devices, and integration with clinical decision support systems.

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