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Adaptive Detection of Cardiac Acoustic Irregularities Using Signal-Driven Intelligence

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Abstract*: Cardiovascular disease (CVD) continues to be a leading cause of death globally, claiming approximately 17.9 million lives each year, as reported by the World Health Organization (WHO). This high mortality rate underscores the need for effective early detection and intervention strategies. Heart sound signals, also known as phonocardiograms (PCGs), hold essential information about cardiac health, providing a non-invasive method to assess heart function. Recent advancements in deep learning have enabled the development of models capable of analyzing heart sounds to detect abnormal features, assisting in early diagnosis and disease prevention. However, the challenges in heart sound data, including imbalanced class distributions, complex feature characteristics, and limited differentiation between sounds like systolic and diastolic murmurs, have restricted the effectiveness of traditional deep learning models. This project presents a novel heart sound anomaly detection algorithm based on the Deep Neural Network Model. The DNN ability to capture both local and global features within a signal makes it particularly well-suited for analyzing heart sound data. The proposed algorithm was tested on the PhysioNet/CinC 2016 public dataset, a widely used dataset for heart sound classification. Experimental results demonstrated a high classification accuracy of 99%, with a specificity of 98.5% and a sensitivity of 98.9%. These metrics signify a substantial improvement over existing methods, highlighting the model's effectiveness in detecting anomalies in heart sounds. The high sensitivity and specificity rates underscore the model's potential to serve as a reliable tool for early screening and diagnosis of cardiovascular diseases.*

Keywords: *Cardiovascular disease*

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of morbidity and mortality worldwide, posing a significant burden on healthcare systems [1], [2]. Early detection and diagnosis are crucial for improving patient outcomes, especially in resource-limited environments with restricted access to medical equipment. Auscultation, listening to heart sounds using a stethoscope, is a simple yet effective tool for assessing cardiac health. However, the accuracy of auscultation largely depends on the experience and skill of the healthcare professional. While cardiologists can achieve high diagnostic accuracy, it is often challenging for general practitioners and non-specialists to make precise diagnoses, which may lead to misdiagnosis or missed diagnoses of diseases [3], [4]. This limitation highlights the urgent need to develop an automated system capable of accurately and efficiently analyzing heart sounds, which would play a crucial role in the early detection of cardiovascular diseases. For example, literature [5] introduces an expert diagnosis system for early-stage heart disease based on fuzzy inference technology. This system demonstrates the potential of fuzzy logic in handling uncertainty and complexity and provides a new perspective for researchers in the field of heart sound classification. By applying fuzzy inference techniques to the processing and classification of heart sound signals, the inherent uncertainty and complexity of heart sound data can be more effectively addressed. This research direction helps improve automated heart sound analysis systems' performance and offers a promising pathway for developing future cardiovascular disease diagnostic technologies. Artificial intelligence technology has recently been widely applied in medical research. For instance, literature [6] proposes a Deep learning neural network (DNN)-based algorithm that utilizes CT scan images to identify lung nodules. The study demonstrates that this algorithm significantly improves the accuracy of lung nodule detection. This suggests that researchers could explore converting time-domain and frequency-domain features of heart sounds into images and apply artificial intelligence techniques to the automated classification of heart sound signals. Such an approach could assist doctors in more accurately assessing patients' cardiac health. By leveraging such systems, diagnostic accuracy can be enhanced while also alleviating the workload of healthcare professionals—an especially valuable benefit in resource-constrained settings where these tools can have a significant impact. Heart sounds, produced by the mechanical actions of the heart throughout the cardiac cycle, carry essential information about the state of cardiac health. A typical cardiac cycle consists of four phases (S1, S2, S3, S4), with S1 and S2 being the most diagnostically significant [7]. Abnormal heart sounds, such as murmurs, may indicate underlying pathologies, including valvular dysfunction and heart failure. Traditionally, feature extraction from heart sound signals has relied on signal processing methods such as time-domain analysis and Mel Frequency Cepstral Coefficients (MFCC), which have been widely used to capture key characteristics of the audio signals. However, these methods exhibit limitations in capturing the complex nonlinear characteristics of heart sounds, especially in noisy environments or when abnormalities are subtle. In recent years, the rapid development of deep learning technologies has revolutionized several fields, including speech recognition, image classification, and medical signal analysis. Deep learning methods, particularly Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have demonstrated exceptional performance in handling complex, high-dimensional data tasks [8], [9], [10]. A vital advantage of these methods is their ability to automatically extract features from raw data, eliminating manual feature engineering commonly required in traditional machine learning approaches. Deep learning models have also shown vital classification accuracy and robustness in capturing the spatiotemporal patterns present in heart sound signals [11]. This study is motivated by two key factors. First, the increasing global burden of cardiovascular diseases (CVDs) demands more efficient diagnostic tools, especially in regions with scarce specialized cardiology services.

II. LITERATURE SURVEY

Title: A review of deep learning for screening, diagnosis, and detection of glaucoma progression
Year: 2023
Authors: ChengAtalie c. Thompson, Alessandro A. jammal, Felipe A. Medeiros.
Description: Because of recent advances in computing technology and the availability of large datasets, deep learning has risen to the forefront of artificial intelligence, with performances that often equal, or sometimes even exceed, those of human subjects on a variety of tasks, especially those related to image classification and pattern recognition. As one of the medical fields that is highly dependent on ancillary imaging tests, ophthalmology has been in a prime position to witness the application of deep learning algorithms that can help analyze the vast amount of data coming from those tests. In particular, glaucoma stands as one of the conditions where application of deep learning algorithms could potentially lead to better use of the vast amount of information coming from structural and functional tests evaluating the optic nerve and macula. The purpose of this article is to critically review recent applications of deep learning models in glaucoma, discussing their advantages but also focusing on the challenges inherent to the development of such models for screening, diagnosis and detection of progression. After a brief general overview of deep learning and how it compares to traditional machine learning classifiers, we discuss issues related to the training and validation of deep learning models and how they specifically apply to glaucoma. We then discuss specific scenarios where deep learning has been proposed for use in glaucoma, such as screening with fundus photography, and diagnosis and detection of glaucoma progression with optical coherence tomography and standard automated perimetry. Translational relevance: Deep learning algorithms have the potential to significantly improve diagnostic capabilities in glaucoma, but their application in clinical practice requires careful validation, with consideration of the target population, the reference standards used to build the models, and potential sources of bias.

Title: Direct cup-todisc ratio estimation for glaucoma screening via semi-supervised learning,
Year: 2023
Author: Rongchang Zhao; Xuanlin Chen; Xiyao Liu; Zailiang Che.

Description: Glaucoma is a chronic eye disease that leads to irreversible vision loss. The Cup-to-Disc Ratio (CDR) is a key indicator in glaucoma screening and plays a crucial role in both clinical assessment and early diagnosis of the disease. Typically, CDR is determined by measuring the optic disc and cup, either through manual or automated segmentation. However, despite considerable research efforts, achieving high accuracy and robustness in automatic CDR estimation remains a significant challenge, primarily due to the substantial overlap between the optic cup and the neuroretinal rim regions. This paper presents a direct approach for estimating the Cup-to-Disc Ratio (CDR) using a semi-supervised learning framework, which eliminates the need for traditional optic disc and cup segmentation. Instead, CDR estimation is treated as a standard regression task. The method leverages deep learning to extract feature representations from the optic nerve head and directly predicts the CDR value without intermediate segmentation steps. The proposed framework follows a two-stage cascaded structure. In the first stage, fundus image features are learned in an unsupervised manner using a convolutional neural network called MFPPNet. In the second stage, these features are input into a random forest regressor to estimate the CDR value. The approach is validated on both the challenging Direct-CSU dataset and the publicly available ORIGA dataset. Experimental results show that the method achieves an average CDR error of just 0.0563 and a correlation of approximately 0.726 with expert-annotated values prior to manual segmentation. Additionally, the predicted CDR values are used for glaucoma screening, yielding an area under the curve (AUC) of 0.905 on a dataset containing 421 fundus images. These results demonstrate the effectiveness of the proposed method in achieving high-precision CDR estimation and reliable glaucoma screening.

Title: ‘Brain inspired dynamic system for the quality of service control over the long-haulnonlinear fiber-optic link.
Author: Alduayj, S. S., & Rajpoot, K.
Year: 2022
Description: Brain-inspired intelligence using the cognitive dynamic system (CDS) concept is proposed to control the quality-of-service (QoS) over a long-haul fiber-optic link that is nonlinear and with non-Gaussian channel noise. Digital techniques such as digital-back-propagation (DBP) assume that the fiber optic link parameters, such as loss, dispersion, and nonlinear coefficients, are known at the receiver. However, the proposed CDS does not need to know about the fiber optic link physical parameters, and it can improve the bit error rate (BER) or enhance the data rate based on information extracted from the fiber optic link. The information extraction (Bayesian statistical modeling) using intelligent perception processing on the received data, or using the previously extracted models in the model library, is carried out to estimate the transmitted data in the receiver. Then, the BER is sent to the executive through the main feedback channel and the executive produces actions on the physical system/signal to ensure that the BER is continuously under the forward-error-correction (FEC) threshold. Therefore, the proposed AIF is an intelligent and adaptive system that can mitigate disturbance in the fiber optic link (especially in an optical network) using prediction in the perceptor and/or doing proper actions in the executive based on BER and the internal reward. A simplified CDS was implemented for nonlinear fiber optic systems based on orthogonal frequency division multiplexing (OFDM) to show how the proposed CDS can bring noticeable improvement in the system's performance. As a result, enhancement of the data rate by 12.5% and the Q-factor improvement of 2.74 dB were achieved in comparison to the conventional system (i.e., the system without smart brain).

III. METHODOLOGY

EXISTING SYSTEM

The Swin Transformer model primarily comprises patch partitions, Swin Transformer blocks, and patch-merging components. The structure of the Swin Transformer is illustrated in Fig 1. The complete Swin Transformer consisted of five stages. In the first stage, the input data are fed into the patch embedding module, where a convolutional layer is utilized to segment the input data into non-overlapping patches. Each segmented patch is defined as a ’token.’ In the second stage, the segmented tokens were input into a Linear Embedding layer, where each token was mapped to a dimension of C (C=96). Subsequently, the tokens enter the two Swin Transformer block modules. This module primarily consists of Layer Normalization, two window based self-attention mechanisms (W-MSA and SW-MSA), and an ((MLP). Within the Swin Transformer Block, self-attention calculations were performed on the tokens. The third stage involves Patch Merging to reduce the number of tokens while reducing their feature dimensions.

EXISTING SYSTEM DISADVANTAGES

- Dependency on Large Datasets: Swin Transformers perform best with large datasets, which may not be available for certain specialized tasks.
- Memory Intensive: Processing large input sizes demands considerable memory, which can limit scalability on devices with limited resources.
- Swin Transformers require longer training times due to the complexity of window-shifted self-attention layers and multi-stage processing.

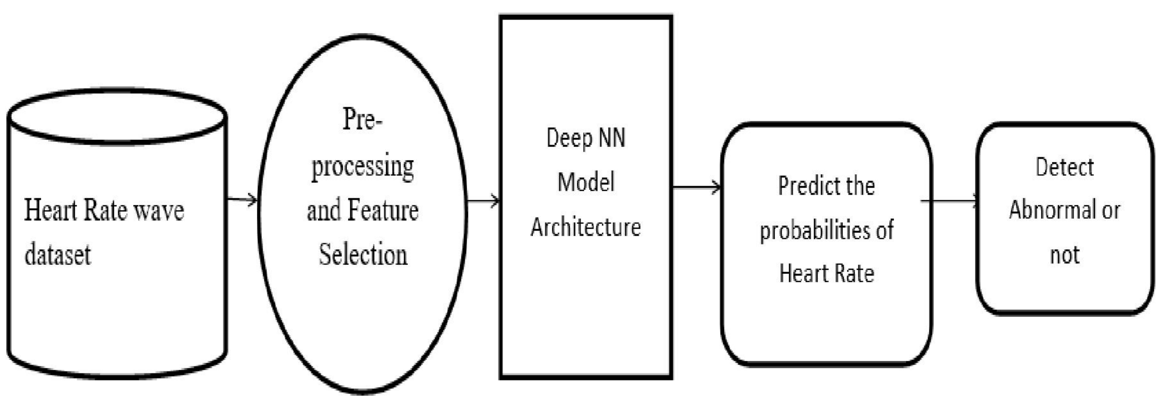
PROPOSED SYSTEM

The proposed approach addresses a critical symptom of many cardiovascular illnesses by using a deep neural network (DNN) to detect heart rate anomalies in real-time. Patient privacy is at stake since heart rate data is frequently presented in unencrypted by traditional telemedicine systems. In order to mitigate this, our method makes use of heart rate data in.wav files and applies a DNN for effective analysis and anomaly detection. The monitoring results may be accessed by users and healthcare experts without disclosing the original heart rate data thanks to the accompanying Flask UI interface, which guarantees a smooth user experience. Our method improves the prompt treatment of cardiovascular issues by enabling early diagnosis and intervention through remote monitoring of heart rate irregularities. Users only receive the final count of anomalies, not the raw heart rate data, therefore this novel solution protects patient privacy while simultaneously prioritizing computational speed. The system's feasibility is validated by the testing results, ensuring a seamless and effective experience for both users and healthcare professionals' problems.

PROPOSED SYSTEM ADVANTAGES

- Automatically extracting relevant features from complex heart rate data, enabling them to identify subtle patterns indicative of arrhythmias with high accuracy.
- Adept at analyzing temporal relationships within the heart rate signals, allowing for the detection of irregularities that may manifest over time.
- Real-time monitoring of heart rate abnormalities, facilitating prompt intervention.

IV. SYSTEM ARCHITECTURE



MODULES:

- **Dataset:** In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the dataset for Arrhythmia detection. The dataset consists of 800 wave files including Arrhythmia and normal.
- **Importing the necessary libraries:** We will be using Python language for this. First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, Numpy for converting the data into array of numbers, Librosa, It provides the building blocks necessary to create the wave files information retrieval systems and other libraries such as tkinter, PIL, matplotlib, os and streamlit.
- **Retrieving the information:** We will retrieve the wave files and their labels. Then resize the waves dataset to default train size as all wave files should have same size for detection. Librosa provides the building blocks necessary to create the wave files information retrieval systems, then convert the information retrieval from wave files into numpy array.
- **Splitting the dataset:** Split the dataset into train and test. 80% train data and 20% test data.
- **Training algorithm**:The training algorithm of the convolution neural network is a backward propagation algorithm based on gradient descent. The network hyper parameters are estimated by the loss function, which is the deviations of the output vector and the expected output vector. Hyper parameters include the convolution kernel parameter W of the convolution layer, the sampling weight coefficient α of the pooling layer, the network weight w of the fully-connected layer and the offset b of each layer. The training of a convolution neural network consists of two phases, forward propagation and reverse propagation. In the forward propagation stage, the training data is input into the neural network, and the output vectors of the middle and output layers are calculated. In the reverse propagation stage, the output vectors of the output layer are compared with the expected output vectors and calculated the loss function with respect to the weights of the network. The loss is propagated back to the initial layers (in reverse direction) using the gradient descent method to update the weights for each neuron in every layer. Gradient descent comprises two steps: calculating gradients of the loss function, which is calculated by chain rules, then updating weight in the opposite or reverse direction of the gradient of the loss function, which is distinct from the forward calculation of loss function. A cost function is also calculated for the neuron output in each hidden layer to optimize the network hyper parameters continuously. The network ends training when it reaches the set error after multiple iterations.
- **Building the model:** For building we will use sequential model from keras library. Then we will add the layers to make our neural network. In the first 1 Conv2D layers we have used 16 filters and the kernel size is (2, 2). In the MaxPool2D layer we have kept pool size (2, 2) which means it will select the maximum value of every 2 x 2 area of the wave files. By doing this values of the wave files will reduce by factor of 2. In dropout layer we have kept dropout rate = 0.25 that means 25% of neurons are removed randomly.We apply these 3 layers again with some change in parameters. Then we apply flatten layer to convert 2-D data to 1-D vector. This layer is followed by dense layer, dropout layer and dense layer again. The last dense layer outputs 2 nodes as the Arrhythmia detection system. This layer uses the softmax activation function which gives probability value and predicts which of the 2 options has the highest probability.
- **Apply the model and plot accuracy:** We will compile the model and apply it using fit function. The batch size will be 128. We got average validation accuracy of 99.6% and average training accuracy of 99.7%.
- **Accuracy on test set:** We got an accuracy of 99.3% on test set.
- **Saving the Trained Model:** Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5 or .pkl file using a library like save or pickle. Make sure you have save/pickle installed in your environment. Next, let's import the module and dump the model into .h5 or.pkl file.

V. IMPLEMENTATION:

SWIN TRANSFORMER ALGORITHM:

The existing system uses the **Swin Transformer** algorithm, which processes input data by dividing it into non-overlapping patches. These patches, referred to as tokens, are passed through a **Linear Embedding layer** that maps them to a fixed dimension (C = 96). The tokens are then processed by **Swin Transformer blocks**, which apply **Layer Normalization**, **window-based self-attention mechanisms** (W-MSA and SW-MSA), and **MLPs** to extract meaningful features. To reduce complexity, a **Patch Merging** step combines tokens while decreasing their feature dimensions. This hierarchical structure helps the model efficiently capture both local and global patterns in the input data.

ARRHYTHMIA INTELLIGENT FRAMEWORK (AIF)/ NEURAL NETWORK:

The core of our proposed technique lies in the implementation of a Deep Neural Network (DNN) for heart rate arrhythmia detection. In the first stage, the.wav files containing heart rate data are input into the DNN, which is designed to automatically extract relevant features and patterns. The Neural network layers of the network perform spatial filtering, capturing intricate details in the heart rate signals. Subsequently, the pooling layers help reduce dimensionality while preserving essential information, enabling the network to discern irregularities effectively. Through backpropagation and optimization, the DNN learns during the training phase to identify patterns linked to both normal and pathological heart rate patterns. The model is optimized to improve the precision with which abnormalities are detected, guaranteeing stable operation in real-time monitoring. The system can assess intricate temporal patterns in the heart rate data thanks to this deep learning technique, which also helps it recognize minute anomalies that can be signs of cardiovascular diseases. Our suggested method offers a sophisticated and automated way to detect aberrant heart rate patterns with great efficiency and accuracy by using a DNN.

VI. EXPERIMENTAL RESULTS:

HOME PAGE

The image shows first screen of the application that presents the home page, where three primary options are displayed: ”Home,” “Register,” and ”About,”. This interface is designed to allow the user to either gain more information about the system or proceed directly to the heart sound anomaly detection process. To initiate the detection workflow, the user selects the ”Register” option.

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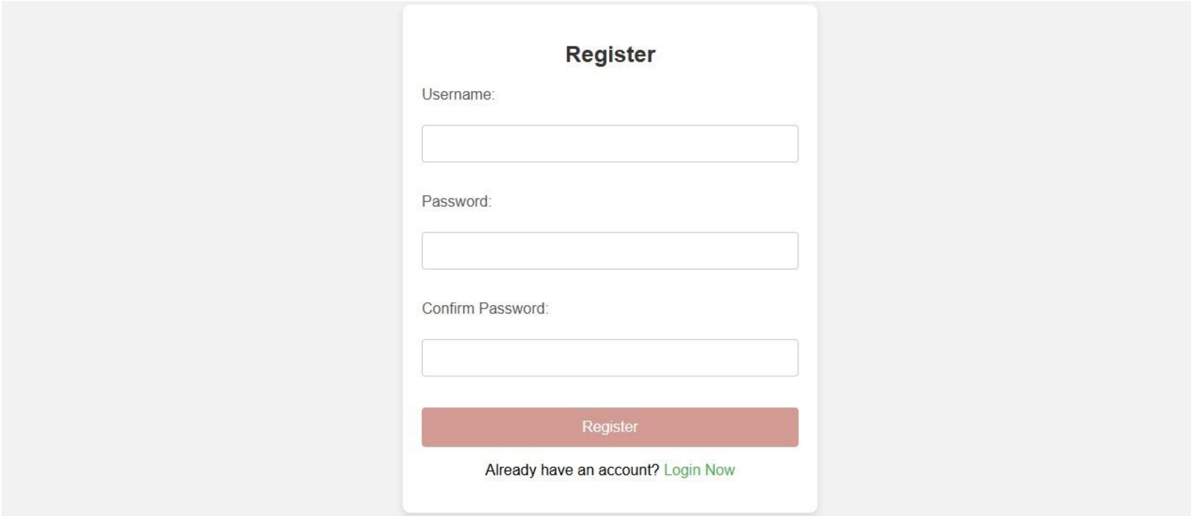
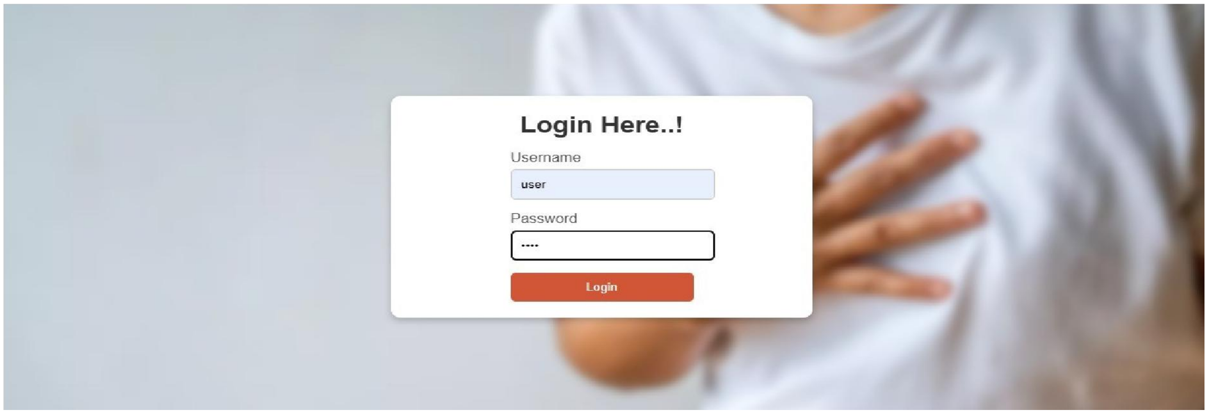
REGISTRATION PAGE:



Upon selecting ”Register,” the system navigates to the next stage where the user is prompted to either login or create new username. After registering click on “Login now” to divert into login page.

LOGIN PAGE:



The image shows login page, where after providing right information about username and password, the user can login successfully.

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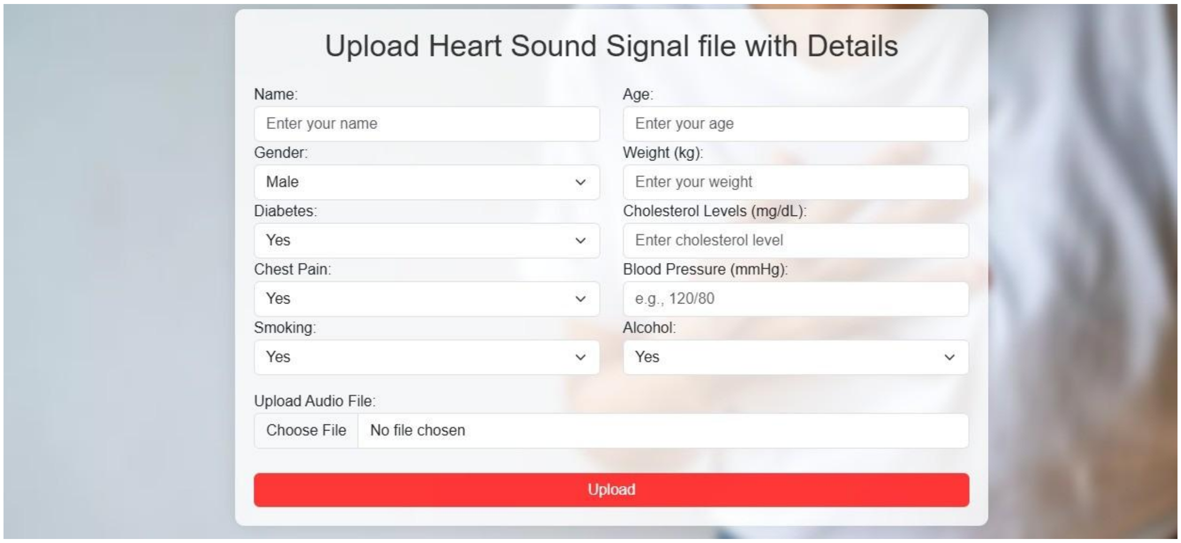
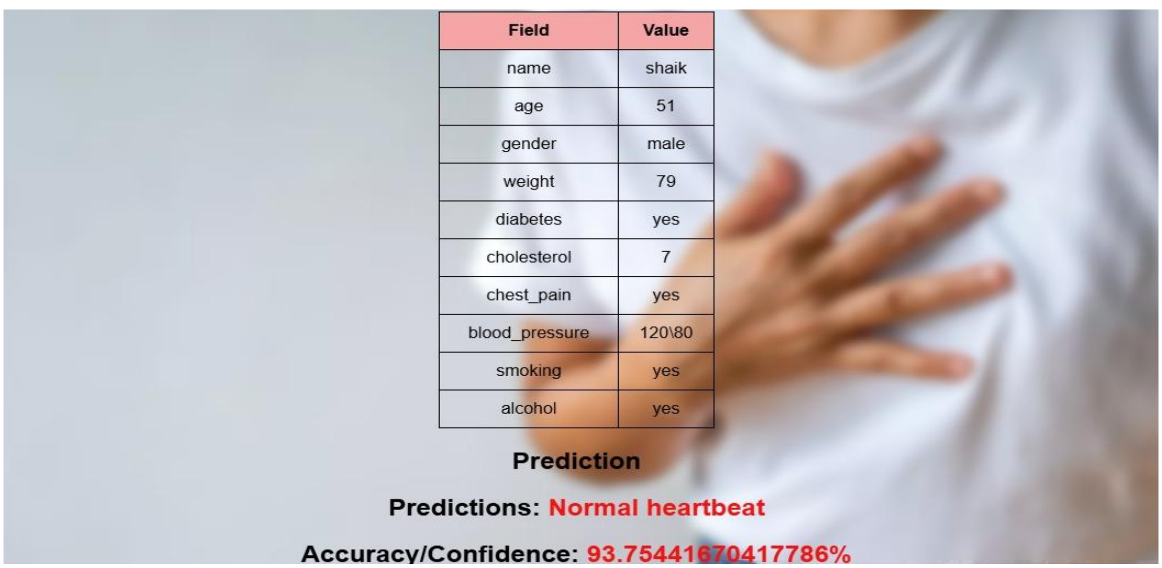
USER INPUT PAGE:



Upon login is successfully, the system navigates to the next stage where the user is prompted to upload a heart sound signal and also provide additional information about health. This input signal serves as the critical data source for subsequent processing. Once a heart sound file is provided, the system automatically.

RESULT PAGE:



The result is displayed clearly, indicating the presence or absence of anomalies within the recorded signal as abnormal or normal heartbeat. This page provides immediate feedback to the user regarding the condition of the heart sound. Subsequently, the system evaluates its performance by calculating metrics such as accuracy.

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VII. CONCLUSION

In this paper, we propose an effective method for detecting abnormal heart sounds. This method includes data preprocessing steps and Deep learning Algorithm Specifically, we designed a fifth-order Butterworth filter to reduce noise interference and adopted the Focal Loss function along with linear interpolation to address the class imbalance between normal and abnormal heart sound samples. Additionally, we utilized Comember instead of traditional Patch Embedding to enhance the model's ability to capture local features of heart sound signals. By incorporating a Discrete Cosine Transform (DCT) structure, we improved the model's capability to capture the correlation between time-domain and frequency-domain features of heart sounds. Experimental results demonstrate that the DCv-Deep learning algorithm exhibits superior performance in heart sound classification tasks. Although significant progress has been made in heart sound classification, there remain several challenges. Future work will focus on improving the model's generalization capabilities and exploring better heart sound signal features to further enhance its performance in practical applications.

FUTURE ENHANCEMENT

In our future work, a AIF for health screening application is proposed and implemented with more number of categories. This AIF incorporates decision-making trees, non-monotonic reasoning, a decision making approach inspired from humans in the case of conflict-of-opinions, prediction using ML classifiers technique health features.In the future, real-time data integration from IoT medical devices can be introduced for dynamic health monitoring. The system can be adapted for mobile platforms to increase accessibility in remote areas. Enhanced visualization tools may be added to help doctors interpret predictions more effectively. Reinforcement learning techniques can be explored to continuously optimize decision-making over time. Moreover, cloud-based deployment can be implemented for scalable and centralized healthcare analytics.

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