ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

EFFICIENT ANOMALY DETECTION ALGORITHM FOR HEART SOUND SIGNAL

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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.

Index Terms – Cardiovascular disease (CVD), heart sound analysis, phonocardiogram (PCG), deep neural network (DNN), heart sound anomaly detection, deep learning, medical signal processing, PhysioNet/CinC 2016 dataset, cardiac diagnosis, healthcare AI, abnormal heart sound classification, early disease detection.

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 doing so, not only can diagnostic accuracy be improved, but the workload of physicians can also be reduced, which is particularly important in resource-limited environments where such systems can play a crucial role. systems can play a crucial role. Heart sounds are generated by the mechanical activity of the heart during the cardiac cycle, and they contain vital information about 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, signal processing techniques such as time-domain analysis and Mel Frequency Cepstral Coefficients (MFCC) have been employed to extract features from heart sound 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. Automated heart sound classification systems have the potential to make early CVD detection more accessible, reducing reliance on expert interpretation and enabling non-specialists to perform diagnoses. Second, the limitations of traditional signal processing techniques in analyzing complex heart sounds highlight the need for more advanced machine-learning models capable of learning directly from raw data. By leveraging the strengths of deep learning, this study aims to overcome the challenges of conventional methods and provide a more reliable and scalable solution for detecting abnormal heart sounds.

The primary objective of this study is to develop a deep learning-based framework for the automatic classification of abnormal heart sounds aimed at facilitating the early detection of cardiovascular diseases (CVDs). Specifically, this research proposes an innovative network architecture that integrates convolutional concepts with the Swin-Transformer, designed to capture both local patterns and long-range dependencies in heart sound signals. Unlike traditional methods that rely on manual segmentation and feature extraction, this approach processes raw heart sound signals directly, using an end-to-end framework to streamline the workflow and reduce the risk of information loss during intermediate steps. Ultimately, we propose the Dcv-Swin Transformer method for efficient heart sound anomaly detection.

The critical contributions of our work are summarized as follows: Introduction of a Swin-Transformer-based Architecture for Abnormal Heart Sound Detection: This model leverages the hierarchical local attention mechanism of the Swin-Transformer to effectively capture both local and global features of heart sound signals. Design of a Fifth-Order Butterworth Filter: This filter significantly reduces the interference of heart sound noise on classification tasks by filtering out high frequency noise.

Development of a Convolutional Embedding Module: This module enhances the model's feature extraction capability by better capturing local features of heart sound signals while preserving the positional information of Mel-spectrogram features. Creation of a Convolutional Mapping Module with Discrete Cosine Transform:

This module uses convolutions with varying strides to obtain the q, k, and v matrices for attention calculation.

It reduces data dimensions and retains frequency domain information, thus improving the model's generalization ability. Incorporation of Focal Loss and Linear Interpolation: This approach effectively addresses the class imbalance between normal and abnormal heart sounds, enhancing the model's classification performance on imbalanced datasets.

II. RELATED WORK

A. *A review of deep learning for screening, diagnosis, and detection of glaucoma progression*

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.

B. Direct cup-todisc ratio estimation for glaucoma screening via semi-supervised learning

Glaucoma is a chronic eye disease that leads to irreversible vision loss. The Cup-to-Disc Ratio (CDR) serves as the most important indicator for glaucoma screening and plays a significant role in clinical screening and early diagnosis of glaucoma. In general, obtaining CDR is subjected to measuring on manually or automatically segmented optic disc and cup. Despite great efforts have been devoted, obtaining CDR values automatically with high accuracy and robustness is still a great challenge due to the heavy overlap between optic cup and neuroretinal rim regions. In this paper, a direct CDR estimation method is proposed based on the well-designed semi-supervised learning scheme, in which CDR estimation is formulated as a general regression problem while optic disc/cup segmentation is cancelled. The method directly regresses CDR value based on the feature representation of optic nerve head via deep learning technique while bypassing intermediate segmentation. The scheme is a two-stage cascaded approach comprised of two phases: unsupervised feature representation of fundus image with a convolutional neural networks(MFPPNet) and CDR value regression by random forest regressor. The proposed scheme is validated on the challenging glaucoma dataset Direct-CSU and public ORIGA, and the experimental results demonstrate that our method can achieve a lower average CDR error of 0.0563 and a higher correlation of around 0.726 with measurement before manual segmentation of optic disc/cup by human experts. Our estimated CDR values are also tested for glaucoma screening, which achieves the areas under curve of 0.905 on dataset of 421 fundus images. The experiments show that the proposed method is capable of state-of-the-art CDR estimation and satisfactory glaucoma screening with calculated CDR value.

C. Brain-inspired intelligence for real-time health situation understanding in smart e-Health home applications

The autonomic computing layer of the smart e-Health home based on a cognitive dynamic system (CDS) can be a solution for improving health situation understanding, reducing the healthcare system costs, and improving people’s quality of life. It can also be a solution for reducing the large number of sudden deaths outside of a hospital due to fatal diseases such as Arrhythmia. Towards this objective, we start from understanding the health situation, by diagnosing healthy and unhealthy persons. For this,we developed a decision-making system that is inspired by the medical doctors (MDs) decision-making processes. Our system is based on a AIF for cognitive decision-making and it can create a decision-making tree automatically. The simple, low complexity algorithmic design of the proposed system makes it suitable for real-time applications. A proof-of-concept case study of the implementation of the AIF was done on Arrhythmia disease. An accuracy of 95.4% was achieved using the proposed algorithms. Also, these algorithms can make a decision in less than 80 ms, and for one User, this includes the time for training. The proposed platform can be extended for more healthcare applications such as screening, disease class diagnosis, prevention, treatment, or monitoring healing.

D. *Brain inspired dynamic system for the quality of service control over the long-haul nonlinear fiber-optic link*

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. PROPOSED METHODOLOGY

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.

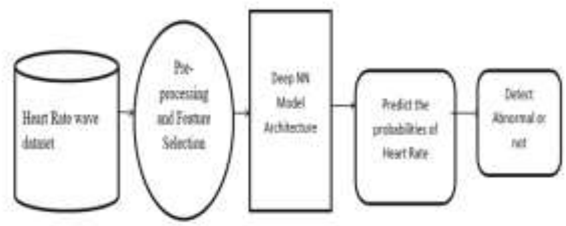

Fig. 1: System Overview

1. 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.

2. 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.

3. 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.

4. Splitting the dataset

Split the dataset into train and test. 80% train data and 20% test data.

5. 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.

6. 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.

7. 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%.

8. Accuracy on test set

We got an accuracy of 99.3% on test set.

9. 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.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results show that the proposed Deep Neural Network (DNN)-based heart sound anomaly detection model achieved 99% classification accuracy on the PhysioNet/CinC 2016 dataset. The model also attained a specificity of 98.5% and a sensitivity of 98.9%, demonstrating reliable detection of abnormal heart sounds. Its ability to capture both local and global signal features significantly improved classification performance over existing methods. Overall, the proposed framework provides an accurate and effective solution for early cardiovascular disease screening and diagnosis.

Fig. 2: Home Page

Fig. 3: Login

Fig. 4: Upload Details

Fig. 5: Prediction Result

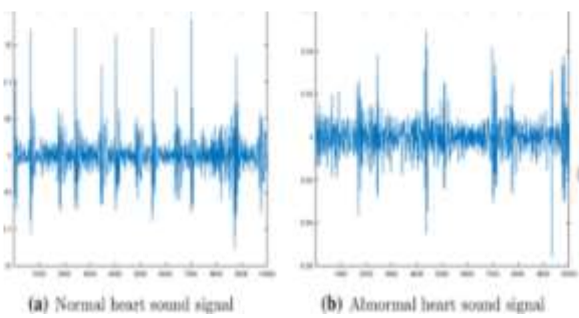

Fig. 6: Accuracy

V. 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 (DDC) 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.

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