



E-HEART DIAGNOSIS

Esther Veronica

Department of Computer Science and Engineering, Loyola ICAM College of Engineering and Technology.

Reah Immaculate*

Department of Computer Science and Engineering, Loyola ICAM College of Engineering and Technology. *Corresponding Author

ABSTRACT Cardiovascular diseases (CVDs) are a major health problem and the early diagnosis of CVDs is crucial as it can incredibly decrease the possible risks associated with the deaths^[1]. All the existing work has either been low accuracy or costly and is not powerful enough for time series analysis data^[3]. Phonocardiogram (PCG) signal represents a high - fidelity recording of sounds and murmurs resulting from heart auscultation^[4]. The phonocardiography (PCG) is an effective and non-invasive method for early detection of cardiac abnormality and the analysis of these PCG signals is critical in the diagnosis of different heart diseases^{[5][10]}. The proposed domain of work is Deep Learning. Deep learning based cardiac auscultation is of significant interest to the healthcare community as it can help reduce the burden of manual auscultation with automated detection of abnormal heartbeats^[2]. However, the problem of automatic cardiac auscultation is complicated due to the requirement of reliable and highly accurate systems, which are robust to the background noise in the heartbeat sound. Therefore, we intend to aid in bringing a precise model for early diagnosis of CVDs, by proposing a Recurrent Neural Networks (RNNs) incorporating the Viterbi Algorithm and Hidden Markov Model (HMM) based automated cardiac auscultation solution. Our choice of RNNs is motivated by their great success of modelling sequential or temporal data even in the presence of noise.

KEYWORDS : Cardiac auscultation, RNN, Viterbi Algorithm, MFCC

INTRODUCTION:

The human heart is responsible for pumping blood throughout the body through the circulatory system, and supplies oxygen and nutrients to the tissues. The heart pumps blood through the network of arteries and veins which is called the cardiovascular system. Cardiovascular disease includes heart conditions involving diseased vessels, structural problems and blood clots. Cardiovascular diseases are the number one cause of death globally, taking an estimated 17.9 million lives each year, says the World Health Organization (WHO)^[1]. Heart disease still ranks the highest in the top 10 causes of death, says a report released on December 9, 2020^[1]. The most intimidating fact is that cardiovascular diseases don't discriminate between adults and children. All are prey to CVDs. Therefore, early diagnosis of cardiovascular diseases is very essential and crucial and it avoids living a falsely normal life. To successfully detect CVDs, different personal health systems have been developed in order to improve detection and collection of data for clinical decision support. Usually, the most common techniques employed for CVD diagnosis are ECG and heart sound (HS) auscultation^{[3][6]}. An auscultation method employed to support clinicians for the objective interpretation of heart sounds is usually utilized to detect four sounds, namely, S1, S2, S3, and S4, during the heart cycle^[9]. The crucial components for signal analysis are S1 and S2, as well as systolic and diastolic periods. The duration of S1 and S2 may help determine the heart sound type and detect abnormal heart sounds, and the amplitude of S1 reveals valuable information about myocardial contractility ability. But some of the heart diseases are hard to detect using ECG because heart sound signals are complex and highly non stationary in nature and are prone to background noises, and it is difficult to examine them in an automated way^[6]. The ascent of phonocardiography (PCG), which is an efficient and non-invasive method for early detection of cardiac abnormality, has addressed the above-mentioned challenges to a large extent^{[5][10]}. In PCG, heart sound is recorded from the chest wall using a digital stethoscope and this sound is analysed to detect whether the heart is functioning normally or the patient should be referred to an expert for further diagnosis if the heartbeat is abnormal^{[5][10]}. PCG signals can deliver significant information relevant to the performance of heart valves, and thus it has high potential for distinguishing several heart diseases by its significant ability to characterize significant features of the heart sounds^{[4][10]}. The PhysioNet Computing phonocardiograms dataset is used and it has produced promising results.

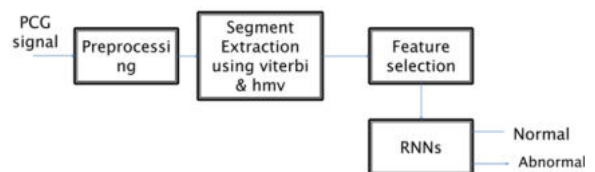
EXISTING WORK :

A deep learning based approach was used for automatic recognition of abnormal heartbeat using a deep Convolutional Neural Network^[6] (CNN). It achieved the highest specificity (true negative rate) score and the sensitivity (true positive rate) and accuracy scores were low. It has relatively high diagnosis speed. All the existing work has either been of

low accuracy or costly and are not powerful enough for time series analysis data^{[3][6]}. The heartbeat interval for a human is a complex time series and the human heartbeat interval is determined by complex nerve control and environmental inputs.

PROPOSED SYSTEM :

Recurrent Neural Networks (RNN) are a type of Neural Network where the output from the previous step is fed as an input to the current step. RNNs are designed to take a series of inputs with no predetermined limit on size. In traditional neural networks, all the inputs and outputs are independent of each other and it is not possible to compute series data. In RNNs all these independent activations are changed to dependent activations because the same weights are provided to every layer thus reducing the complexity of increasing parameters. RNN has a memory that stores all the information from the past and all its decisions are influenced by what it has learnt from the past. The recurrent neural networks (RNN) are helpful in modelling sequence data in the detection of abnormal heartbeats. Recurrent neural networks are specialized to process sequences, unlike the CNNs, which are specialized for gridlike structures, such as images^[6]. RNN is comparatively slower compared to CNN, but since we are dealing with heartbeat classification and analysis, it is more rational to adhere to accuracy than the speed of the algorithm as it deals with human lives^[6]. The Viterbi algorithm is a dynamic programming algorithm that is incorporated in the Hidden Markov Model for finding the most likely sequence of hidden states. The goal is to discover the most optimal sequence of state transition. The HMM has 'X' hidden states and the process depends on these unobservable states. The transition between the 'X' hidden states in the HMM based on different probabilities is determined by the Viterbi Algorithm.

SYSTEM ARCHITECTURE :**PREPROCESSING :**

The phonocardiograms are recorded using sensors placed at the four locations namely the pulmonic area, aortic area, mitral area, and tricuspid area^[3]. It allows the detection of subaudible sounds and murmurs, and makes a permanent record of all these events. The heart sound is first preprocessed for first and second heart sounds (S1 and S2, respectively)^[9]. The most common preprocessing technique for PCG signals is passing the signals through suitable filters^[3]. The median filter is used for the preprocessing of these signals.

SEGMENT EXTRACTION :

The segment extraction is done by incorporating the Viterbi algorithm along with the Hidden Markov Model. The Viterbi algorithm is used for the state transition, brought about by a set of probabilities called transition probabilities. Localization of heartbeat sounds must be done before any analysis. The duration of S1 and S2 helps to determine the heart sound type and to detect abnormal heart sounds, and the amplitude of S1 reveals valuable information about myocardial contractility ability. The location of the beginning of each heartbeat is analysed and is segmented for every cycle into S1 And S2 respectively.

FEATURE SELECTION :

Feature Selection is the process where those features which contribute most to the output variable are selected automatically or manually. This is crucial because having irrelevant features in the data can decrease the accuracy of the model and also decrease its efficiency. We use the Mel-frequency cepstral coefficients (MFCCs) to extract the features from the signal. Mel-frequency cepstral coefficients (MFCCs) are used to identify the components of the heartbeat signal that are good for identifying the aberrations in the heartbeat and discards all the other stuff which carries information like background noise and other sound murmurs. The heartbeat signal is a periodic signal. The difference between the cepstrum and the mel-frequency cepstrum is that in the Mel Frequency Cepstral, the frequency bands are equally spaced on the mel scale, and this approximates the human auditory system's response more closely than the linearly-spaced frequency bands that are used in the normal cepstrum in the analysis of heartbeat signals. An audio signal is constantly changing. On short time scales the audio signal doesn't change much but if it is longer the signal changes too much throughout the frame. So, we process the heartbeat signal and place them into short frames. Initially, the signals are framed into short frames. For each frame the periodogram estimate of the power spectrum is calculated. This enables us to discern the difference between two closely spaced frequencies. As the frequencies in the signal increase, this becomes tedious. For this reason, we take the sum to calculate the energy present in the various frequency regions. Therefore, we consider clumps of periodogram bins and sum them up to get an idea of how much energy exists in various frequency regions. Finally, the Mel-Filter is applied to the power spectrum. To calculate filterbank energies, we multiply each filterbank with the power spectrum, then add up the coefficients. This filter is very narrow and gives an indication of how much energy exists in the lying frequency regions. The logarithm is applied to all of the filterbank energies followed by taking the Discrete Cosine Transform(DCT) of the log filterbank energies. The logarithm allows us to use cepstral mean subtraction, which is a channel normalisation technique. The DCT is taken because our filterbanks are quite correlated with each other. The DCT decorrelates the energies which means diagonal covariance matrices can be used to model the features in e.g. a HMM classifier. This frequency warping allows for better representation of heartbeat sound. Incorporating the Mel Scale makes our features match more clearly what humans generally hear in order to obtain accurate results. The prime features are selected and the signals are processed into arrays^{[7][8]}. Then, the output arrays are fed into the RNNs.

RNN :

Unlike CNNs that accept a fixed size input and produce a fixed size output, RNNs are effective because they are suitable for time series data and can remember the output of one stage to be fed in as an input to the next stage. The network itself takes care of many of the filtering and normalization tasks that must be completed by human programmers when using other machine learning techniques. A softmax function is used to project the output vector into the probability vector having values in [0,1]. When the RNNs are used for abnormal heartbeat detection, its end layer is projected to the number of classes namely normal and abnormal.

OUTPUT :

The PCG signal pattern differs with respect to heart disease, especially which are related to valve functionality^[4]. A big difference in the pattern and the shape can be noticed between the normal and abnormal heart sound as their signal varies from disease to other with respect to amplitude, time, intensity, and frequency of every cycle.

The sensitivity score of the CNN model was found to be 0.7279 whereas in this work, using RNN, we find that the sensitivity score is 0.9889 which enhances the certainty of the motive. The accuracy rate is relatively higher than the existing models and it is very powerful for time series data.

CONCLUSION:

The empirical studies conducted proves that the abnormal heartbeat detection using the PCG signals and the RNN (recurrent neural network) produce results that are very promising. In particular, the results are significantly better than the existing conventional deep learning models that use Convolutional Neural Networks(CNNs)^[6]. It is predicted to decrease the percentage of human loss caused by cardiovascular diseases as this method aids medical professionals in the early diagnosis of such CVDs.

REFERENCES :

- [1] Bulletin of World Health Organization, December, 2020
- [2] S. Latif, J. Qadir, S. Farooq, and M. A. Imran, "How 5g wireless (and concomitant technologies) will revolutionize healthcare?" *Journal Future Internet*, vol. 9, no. 4, p. 93, 2017.
- [3] "How Much Does an EKG Cost?" "A. A. H. Care
- [4] P. Wang, C. S. Lim, S. Chauhan, J. Y. A. Foo, and V. Anantharaman, "Phonocardiographic signal analysis method using a modified hidden markov model," *Annals of Biomedical Engineering*, vol. 35, no. 3, pp. 367–374, 2007.
- [5] M. Nassralla, Z. El Zein, and H. Hajj, "Classification of normal and abnormal heart sounds," in *Advances in Biomedical Engineering (ICABME)*, 2017 Fourth International Conference on. IEEE, 2017, pp. 1–4.
- [6] Mohammad Mahmudur Rahman khan, Md. Abu Bakr Siddique, Shadman Sakib, Anas Aziz, Abyaz Kader Tanzeem, Ziad Hossain "Electrocardiogram Heartbeat Classification using convolutional Neural Networks for the Detection of Cardiac Arrhythmia(2020)" 4th International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC 2020), IEEE, 7-9 October 2020
- [7] L. Avendaño-Valencia, J. Godino-Llorente, M. Blanco-Velasco, and G. Castellanos-Dominguez, "Feature extraction from parametric time–frequency representations for heart murmur detection," *Annals of Biomedical Engineering*, vol. 38, no. 8, pp. 2716–2732, 2010.
- [8] Y. Zheng, X. Guo, and X. Ding, "A novel hybrid energy fraction and entropy-based approach for systolic heart murmurs identification," *Expert Systems with Applications*, vol. 42, no. 5, pp. 2710–2721, 2015.
- [9] H. Uguz, "A biomedical system based on artificial neural networks and principal component analysis for diagnosis of heart valve diseases," *Journal of medical systems*, vol. 36, no. 1, pp. 61–72, 2012.
- [10] Amir Mohammad Amiri and Giuliano Armano, "Detection and Diagnosis of Heart Defects in Newborns Using CART ", University of Cagliari/Department of Electrical and Electronic Engineering (DIEE), Cagliari, Italy, July 2013 *Journal of Life Sciences and Technologies* 1(2):103-107.