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Hybrid Deep Learning Assisted Neonatal Bradycardia Detection Using Ensemble Features of ECG Recording

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Abstract— *Neonatal bradycardia occurs when the resting heart rates are under 80 beats per minute. The bradycardia mechanisms includes abnormalities in sinus nodeand irregularities of atrioventricular transmission. This paper proposed Hybrid Dense Attention Cascaded Long Short Term Memory (HybDcL)to detect the Neonatal Bradycardia. In this work, we take input data from Preterm Infant Cardio-respiratory Signals (PICS) databasefor the normal and bradycardia ECG signals. Initially, the input ECG signal is pre-processed by the three stage Discrete Wavelet Coefficient Based Inverse Transform (DwavIT) approach. This method is performed to improve the signal quality by suppressing the noises. Then the pre-processed signals are provided for feature extractor byQ-tune empirical variational component analysis (QEmVaC) model. In the feature extractor model, for obtaining a set of feature vectorsthe Q-tune wavelet transform (QWT), Variational mode decomposition (VMD), empirical mode decomposition (EMD) and Independent component analysis (ICA) are utilized to extract the features. The MAE value of the proposed method is 0.008%, while comparing with other existing methods our proposed method yields better performance. This model is more effective using the hybrid deep learning methodologies for gaining enhanced prediction results*.

Keywords: Deep Learning, Neonatal Bradycardia detection, Discrete Wavelet Transform, Variational Mode Decomposition, Long Short Term Memory, Manta Ray Optimization, Empirical Mode Decomposition, Independent Component Analysis

I. Introduction

Neonatal diseases are among the major reasons of morbidity and an important contributor towards under-five mortality rates in the world [1]. The neonatal duration is a complex situation in human life when a new-born infant has to come up with the fresh environment and diverse physiological changes that are highly needed for life [2-3]. The emergence of neonatal prematurity happens at a rate of 10% worldwide that is defined as less than 37 weeks of gestational age. The growth disorders can be experienced in case of these infants which can lead over impaired health situations [4]. The general syndrome noticed in most of the preterm infants are persistent episodes of apnea and bradycardia [5]. Apnea indicates the absence of breathing in a neonate over the period of greater than 15 seconds. Bradycardia is a condition where the heartbeat of neonates beats less than 60 times per minute. Because of these disorders, end organ damage may generate that are associated to ischemia or minimized flow of blood and hypoxemia or minimized oxygenation of blood.

Due to these variations, oxygenated haemoglobin delivery, reduced cerebral blood velocity and minimized metabolic by-products clearance are resulted [11]. In case of preterm neonates, heart rate information tends to be the most significant clinical indicator as it acts as a complex physiological procedure that influences every organ systems [12-13]. The most commonly used convenient approaches by the surgeons are auscultation and palpation methods but it does not generate precise outcomes compared tophotoplethysmography (PPG) and electrocardiography (ECG) based methods [14]. Certain preventive methodologies like maternal immunization targets on maternal health before birth to guarantee a healthy pregnancy [15]. In terms of curative methodologies, the diagnostic tools are limited and the diagnosis period is longer that leads over declined neonate’s condition

II. Motivation

The premature neonates are subjected to bradycardia influenced by a huge number of factors including immature respiratory development and sepsis. As an efficient physiological indicator, the heart rate possess greater significance in neonatal health observation in neonatal intensive care unit. The present golden standard of heart rate monitoring is dependent upon the PPG or ECG signals evaluated using ECG sensors or PO. The recordings of heart rate variability was carried out at home at term equivalent age. The heart rate variability metrics were associated between diverse transfer periods. The performance of heart beat detection were then associated with standard surface leads. All these researches are motivated to propose a new and effective deep learning based neonatal bradycardia detection that can provide highly accurate results than the existing techniques

The rest of this paper is structured as follows: Section II delivers recent related works, Section III carries proposed methodology for detecting neonatal bradycardia. Section IV contains results and discussion comparing proposed with several existing methodologies, and Section V presents the conclusion

III. PROPOSED DESIGN

One of the critical problems in preterm neonates is bradycardia that signifies the slower heart rate indicating low oxygen levels in blood compared to the normal heart rate. The neonates suffering from bradycardia heart disease possess lower heart rates tending towards blood velocity reduction that can be traversed over developing organs. To mitigate long term effects of bradycardia, early detection is thus highly crucial. As preterm neonates are consistently monitored, the sudden movements generate motion artefacts which leads over inaccurate results. In most of the existing researches, the ECG signal prediction is found to be highly complex because of irrelevant features and inappropriate training ability. Hence in the proposed research work, a novel DL methodology for bradycardia detection from preterm neonates is presented. The block diagram of the proposed work is shown in Figure 1.

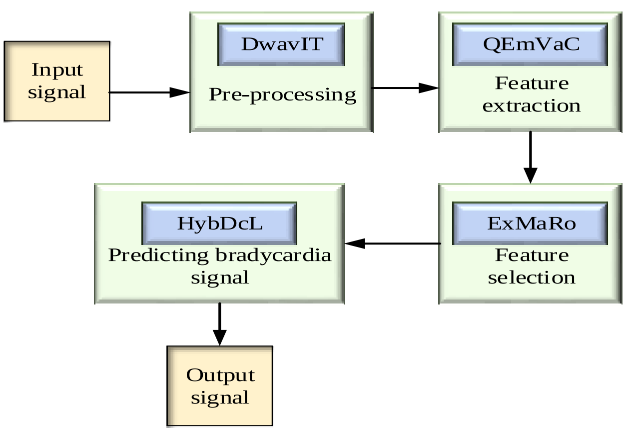

Figure 1: Block diagram of the proposed work

Initially, the ECG signal data are collected from PICS database which are subjected to pre-processing to enhance the signal quality by suppressing the noises. The ECG signals length is checked in the pre-processing stage and every ECG signal contains certain amount of heartbeats and numerous samples

Noise removal from ECG signals using DwavIT:

To separate signal features, it is essential to clean noise from some digital signal that is misleading by sounds of changing nature. An ECG signal explicitlybiased by noise can be written as:

$$N(l)=R(l)+M(l) \tag{1}$$

Where, noise on ECG signal is $M(l)$, $N(l)$ denotes the ECG signal, ECG signal devoid of noise alteration is signified as $R(l)$.

From a signal the noise is eliminated by using the common method called Wavelet transform.The symlet clan of a discrete wavelet transform (DWT) is utilized to clean the noise from ECG signals that is a Daubechies wavelet by the minimum asymmetry and a dense carrier

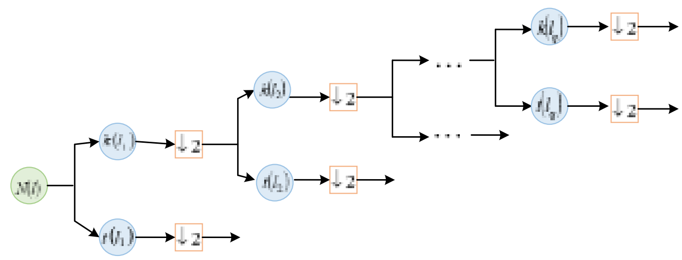

Figure 2: DWT ECG signal

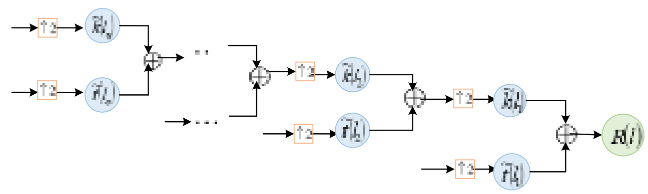

Figure 3: Inverse DWT ECG signal

For eliminating the artefacts from fECG signal the EMD is appropriate and alsoappropriate for the non-stationary signals and non-linear signals. The purpose of this process is to molder the signal intooscillatory functions. The low-frequency modules are known as residues, and high-frequency modules are known as Intrinsic Mode Functions (IMFs). From the uppermost to lowermost the algorithm sorts tasks by means of frequency. For the method to function correctly there contains two conditions. In the first condition, the amount of local excessesneed be similar as the amount of zero crossings at best by single. And in the second condition, the mean value of envelopes at several point are demarcated by the local minima and local maxima thatneed to be zero. The shifting method is known as progression of signal decomposition into IMFs.

Initially, it is essential to detect the entire local minima and local maxima of input signal $z(l)$. Next, to produce proper envelopes by connecting all maxima, the upper envelop $c_{\max}(l)$ as a cubic spline and also by connecting all minima, it is

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essential to make lower envelop $c_{\min}(l)$ as a cubic spline. The mean of envelops is dogged by the below Equation (16):

$$u_{01}(l) = \frac{(c_{\min}(l) + c_{\max}(l))}{2} \quad (2)$$

From the input signal $z(l)$ the mean value is detracted. According to the below Equation (17) the first proto-IMF $r_{01}(l)$ is gained.

$$r_{01}(l) = z(l) - u_{01}(l) \quad (3)$$

Regrettably, it does not frequently happen that the $r_{01}(l)$ module be eligible for IMF and at this moment it is discernible as proto-IMF. The procedures from above specified is must be reiterated and it is symbolized as follows:

$$r_{mp}(l) = r_{m(p-1)}(l) - u_{mp}(l) \quad (4)$$

Where, the index of haul out IMF is denoted as m, p signifies the iteration index. The process is reiterated till the signal size $r_{mp}(l)$ becomes constant. It is essential to describe the stopping criterion for this reason. By the guess of standard deviation σ the stopping criterion method is demarcated.

The normal and bradycardia signals can be predicted effectively using efficient DL model called Hybrid Dense Attention Cascaded Long Short Term Memory (HybDcL). Figure 4 denotes the block diagram of HybDcL for predicting the bradycardia signal

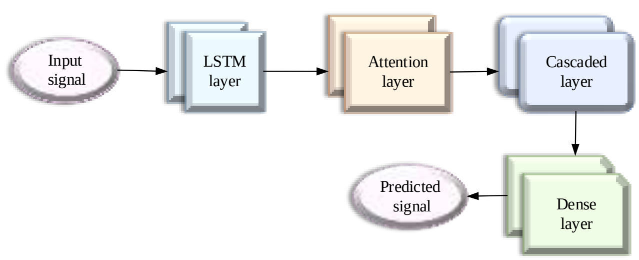

Figure 4: Block diagram of HybDcL

IV. SIMULATION RESULTS AND DISCUSSIONS

This section presents the results and analysis of the proposed technique. Here, simulation is performed by using Python tool. Total amount of data's present in the Preterm Infant Cardio-respiratory Signals (PICS) database is one lakh documents with ten infants. From this database ten thousand documents with one infant data's are utilized for this work. Some of the sample ECG signal with several timestamp is mentioned in the below table 1.

Table 1: ECG data for each timestamp

Timestamp	ECG signal
0	15148
1	15142
2	15142
3	15148
4	15142

In this section, the results and analysis of the proposed method and the comparison of the proposed technique with existing methods is discussed. Also, the comparison of the proposed model with existing techniques like Dense Cascaded LSTM, Attention Cascaded LSTM, Dense Bi-LSTM, Dense Cascaded network. The below Figure 5shows the comparison of training accuracy and loss arcs of proposed method with existing method by varying the epoch values

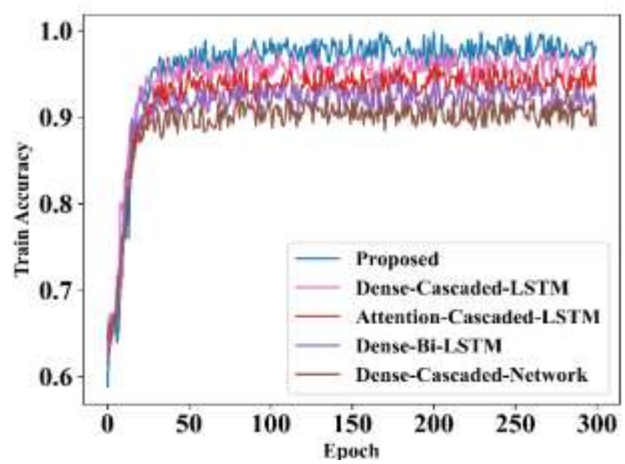

Figure 5. Comparison of training accuracy and loss of proposed with existing method

The above figure shows the comparison of training accuracy and loss arcs of proposed with existing method by varying the epoch values. From this figure, when the epoch value is zero for the proposed method the training accuracy value starts increasing from 0.6, and when the epoch value is greater than 50 the training accuracy value reaches its peak as greater than 0.9 training accuracy value and remains same for the succeeding epoch values. Hence it is inferred that the proposed work attains enhanced training accuracy for greater epoch values than the existing method

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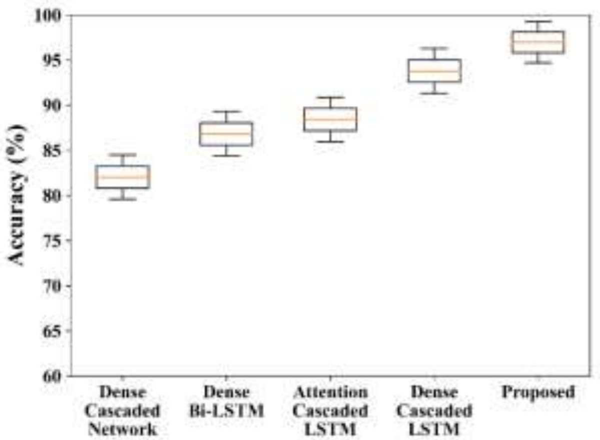

Figure 9. Accuracy comparison of proposed with existing work

The above figure indicates the accuracy comparison of proposed method with existing methods like Dense Cascaded LSTM, Dense Bi-LSTM, Attention Cascaded LSTM, and Dense Cascaded Network. From this figure, it is inferred that the accuracy value of proposed method is 0.992%, Dense Cascaded LSTM attains accuracy value 0.954%, the accuracy of Dense Bi-LSTM is 0.884%, Attention Cascaded LSTM gains 0.9% accuracy, and the accuracy value for Dense Cascaded Network is 0.836%. Hence, it is proved that the accuracy value of proposed method is higher when compared with the existing method. Figure 10 represents the precision comparison of proposed method with existing method.

V. *Conclusion*

In this paper, we proposed a new Hybrid Dense Attention Cascaded Long Short Term Memory for predicting the normal and bradycardia signals from ECG signals. In the pre-processing method by using DwavIT modelthe noises from the input signal is suppressed to improve the signal quality and effective noise removal. Then the pre-processed signal is provided to QEmVaC model to extract the features for obtaining a set of feature vectors. Next, the optimal features are selected by using ExMaRo algorithm for the feature dimensionality minimization and improve the learning abilitywith less rates of error. For predicting the normal and bradycardia signals from the ECG signals the HybDcL model is used. The proposed model provides lower optimization for MSE of 0.008%, RMSE of 0.08%, and MAE of 0.008% and gains higher optimization for F1 Score of 0.992%, accuracy of 0.99%, and precision of 0.992%.

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