A MODIFIED DEEP MACHINE LEARNING METHOD FOR CLASSIFYING CYCLIC TIME SERIES OF BIOLOGICAL SIGNALS USING TIME-GROWING NEURAL NETWORK

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Abstract: A novel strategy for taking in the cyclic substance of stochastic time arrangement: the profound time-developing neural system. The DTGNN consolidates administered and unsupervised strategies in various levels of learning for an upgraded execution. It was utilized by a multiscale learning structure to group cyclic time arrangement (CTS), in which the dynamic substance of the time arrangement are protected in a proficient way. This paper recommends a precise methodology for finding the outline parameter of the characterization strategy for a one versus-different class application. A novel approval technique is additionally proposed for assessing the auxiliary hazard, both in a quantitative and a subjective way. The impact of the DTGNN on the execution of the classifier is measurably approved through the rehashed irregular sub inspecting utilizing distinctive arrangements of CTS, from various therapeutic applications. In this paper Respiration dataset and ECG signals are tested and out of these signals average respiration rate 18.25 is achieved.

Keywords: CTS, DTGNN, signals, EEGs and ECG etc.

I. INTRODUCTION

Time series classification has been a topic of study over decades. Several supervised and unsupervised methods have been suggested with which to learn the dynamic contents of time series. Dynamic time warping, hidden Markov model (HMM), and artificial neural network are three well known methods extensively employed in many contexts, e.g., automatic speech recognition [1]–[3]. Nevertheless, the development of a classification method sophisticated for the cyclic time series (CTS) had been overlooked in the model level, even though a number of methods were subjectively applied to the CTS [4]–[6]. A CTS is described as a nonstationary time series exhibiting repetitive characteristics. Unlike periodic time series, the cyclic duration of a CTS can be inconsistent, but repetitive patterns are observed. This cyclic behavior attributes special features to the time series that can be exploited by a classifier to enhance its classification performance. The importance of developing a sophisticated method for the CTS classification is realized when considering that a recording of many natural phenomena and biological activities resembles a CTS. As an example, phonocardiogram (PCG) is a recording of the sounds emanating from the mechanical activity of a heart. This is considered as a typical CTS where the cycle duration is affected by a number of physiological activities, e.g., respiration. Several studies reported the importance of having a reliable decision support system for screening pediatric cardiac disease in primary healthcare centers, as the screening accuracy is still considerably low [7], [8]. The main challenge for developing a decision support system for screening cardiac disease is a reliable method for processing and classifying the PCG signal. Such a need is seen in different medical applications, in which the biological signal is cyclic, and the classification of the signal can be important, and sometimes critical to patient monitoring, as is the case, for instance, with the classification of the patterns associated with electroencephalograms (EEGs). Biological signals with cyclic characteristics often show nonstationary behavior not only within the cycles, but over them in the cycle-to-cycle variation. This associates a high level of complexity with the signal that makes the development of the classifier, a big challenge. Unlike many industrial applications, the origin of the complexities in the majority of the biological signals has yet to be fully understood. As a result, the stochastic models can provide a better learning than deterministic ones, especially when it comes with a general model for diverse medical applications. Such a model needs to be capable of coping with the complexities of the signals.

II. DEEP NEURAL NETWORKS

The basic structure of DNNs consists of an input layer, multiple hidden layers, and an output layer. Once input data are given to the DNNs, output values are computed sequentially along the layers of the network. At each layer, the input vector comprising the output values of each unit in the layer below is multiplied by the weight vector for each unit in the current layer to produce the weighted sum. Then, a nonlinear function, such as a sigmoid, hyperbolic tangent, or rectified linear unit (ReLU) [3], is applied to the weighted sum to compute the output values of the layer. The computation in each layer transforms the representations in the layer below into slightly more abstract representations [4]. Based on the types of layers used in DNNs and the corresponding learning method, DNNs can be classified as MLP, SAE, or DBN.

MLP has a similar structure to the usual neural networks but includes more stacked layers. It is trained in a purely supervised manner that uses only labeled data. Since the training method is a process of optimization in high-dimensional parameter space, MLP is typically used when a large number of labeled data are available.

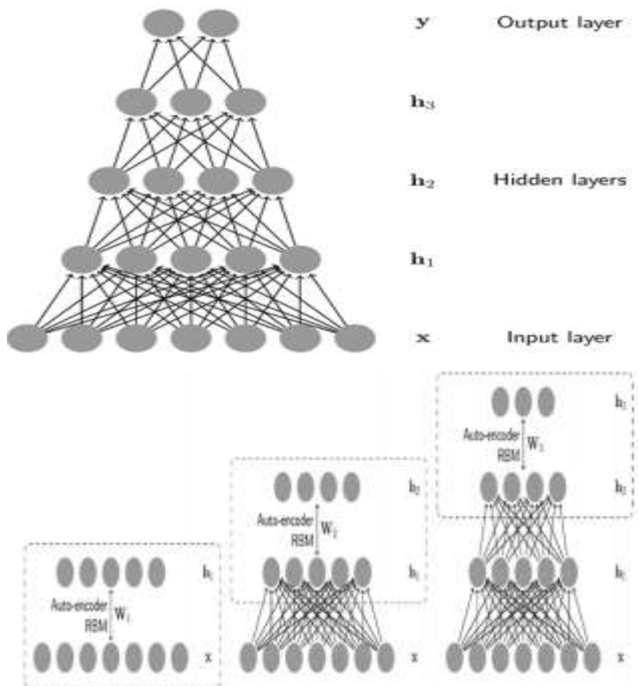

Figure 1.

III. RESEARCH METHODOLOGY

The proposed classifier is sophisticated to overcome the complexities that exist in CTS of biological signals. It introduces three levels of learning: within the cycles, over the cycles, and the time series classification. The first two levels cope with the nonstationary behaviors of the biological CTS, while the last one performs the one-versus-multiple class learning. The dynamic contents of the time series are explored by using the growing sectors in all three schema as introduced. The learning process is based on the spectrasectoral contents of the growing sectors. Fig. 4.1 demonstrates two cycles of a time series along with the growing schema with K = 4 sectors. The number of the growing sectors is considered as a design parameter is found in the optimization process. The method proposes an algorithm for finding an optimal growing center. For a certain sector of a cycle, the spectral contents are calculated over the corresponding sectors of the other cycles. The resulting spectra-sectoral contents are employed for the cyclic learning. The proposed classifier pays special attention to the cyclic learning by introducing a novel learning method, the DTGNN to improve the discrimination power.

the classification process along with its flow mapping by means of a block diagram. As we will see in the sequels, the DTGNN preserves the dynamic content of the cycles in a concise form, which will, in turn, decrease the structural risk, in contrast to the existing methods in which the cyclic behavior is neglected. The DTGNN is based on learning the cyclic contents of CTS by introducing sectoral discriminative frequency bands (SDFBs) defined as those frequency bands whose sectoral energy provides an optimal segregation between the classes. This level of learning is boosted by a preprocessing phase in which an effective sectoral profile is identified. The outcomes of this level of learning constitute the input layer of the TGNN proposed for the cyclic learning. vector quantification technique, using a nonlinear and dynamic method, where the learning process is performed at the input layer to select proper dynamic characteristics and in the middle and output layers for the quantification. In the third level, the outcomes of the TGNN are employed by a binary classifier after the statistical processing. The supervised learning in both the second and third levels utilizes the binary label qi defined in (7) for the classification. The learning process is composed of a multiscale method for enhanced training, and a systematic procedure is proposed to determine the optimal set of design parameters.

IV. RESULT & DISCUSSION

In the research work the different snap shorts are displayed with different respiration wave signals and Camera. These snap shorts are given below:

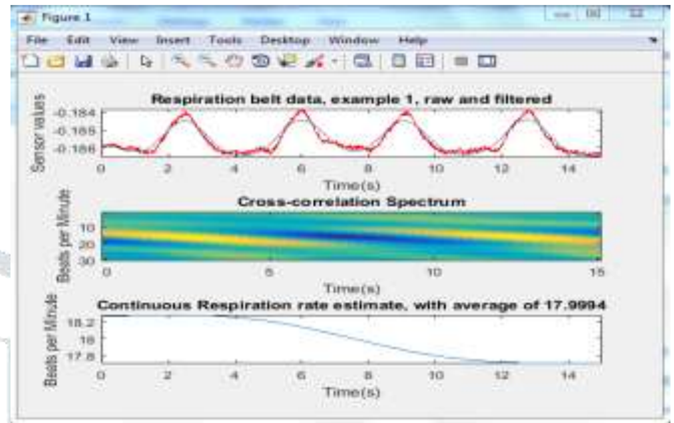

Figure 2: respiration belt data with average 17.9994

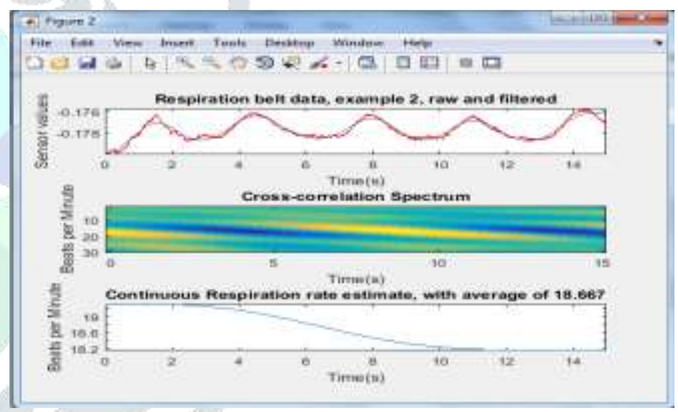

Figure 3: respiration belt data with average 18.667

The figure 2 and the figure 3 is the processing of respiration belt with different average. It displays the cross correlation spectrum and continuous respiration rate estimation.

In the figure 5.1 respiration belt data 1 is displayed. Inside that signal filtered and original is given. The cross correlation is given in this figure. The respiration belt data with average is 17.9994. But in the figure the respiration belt data with average is 18.667. The continuous respiration rate estimation graph is displayed.

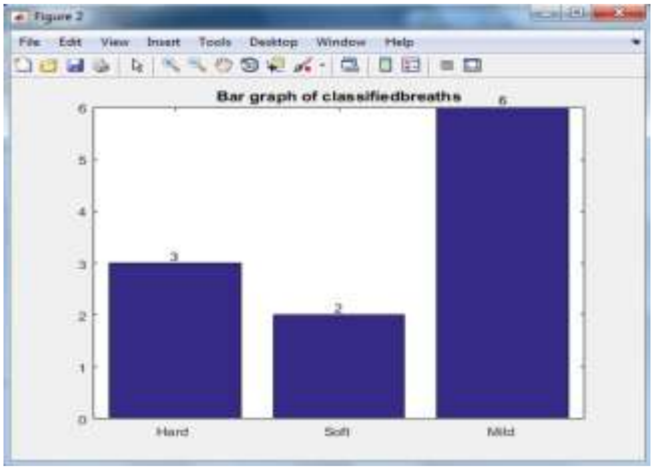

Figure 4: Bar Classification of breath on 1.wav signal

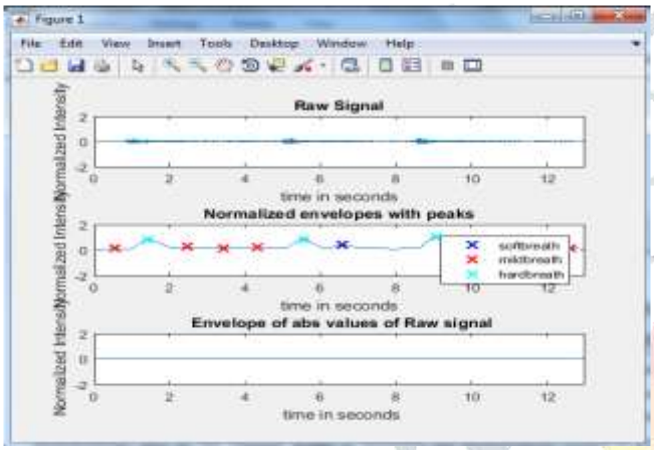

Figure 5: 1.wav breath signal processing

The figure 4 and the figure 5 displays the 1.wav signal processing with soft ,mild and hard breath . it displays the different wave signals that is displayed in the figure.

The figure 5.3 is displaying the three bar graph strips. Out of these one is the hard, soft and mild signal strip. It is detected from the respiration signal. The figure 5.4 is the 1.wav breathe signal processing. In this figure the original strip is the raw signal and other displaying the hard, mild and soft breath signal.

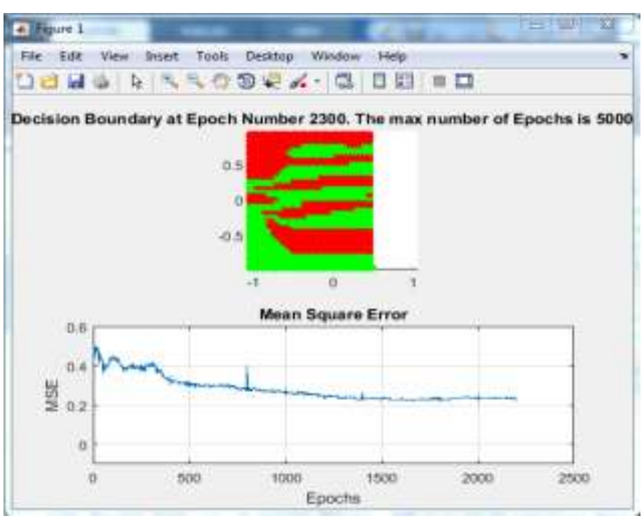

Figure 11: Deep Neural Network processing

The figure 11 is the Deep Neural Network Processing. In this figure decision boundary at Epoch Number 2300 is displayed . The maximum epoch is 5000. Here MSE and Epoch graph is displayed.

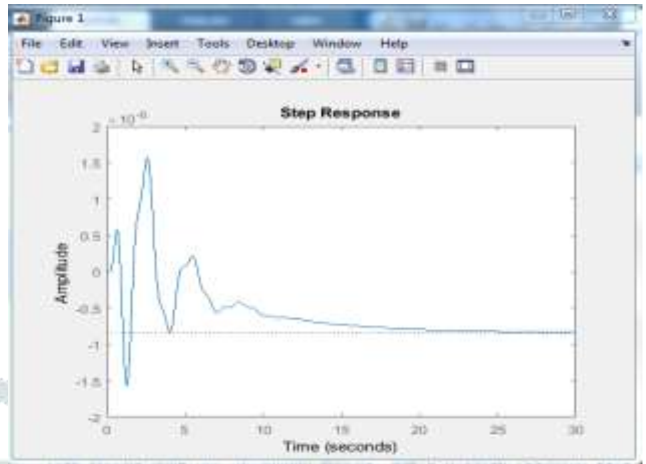

Figure 12: Neural Network processing

The figure 12 is the Neural Network Processing. In this graph Amplitude and Time of signal is defined. The amplitude is varied with Time.

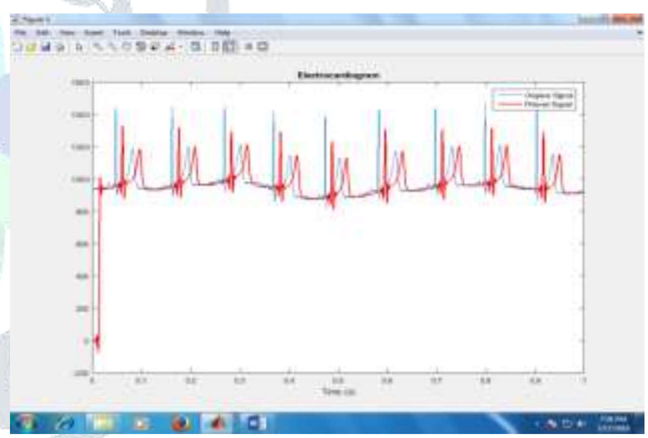

Figure 13: original signals

The figure13 is defined the original ECG signal; Here in this figure filtered and original ECG signal is defined.

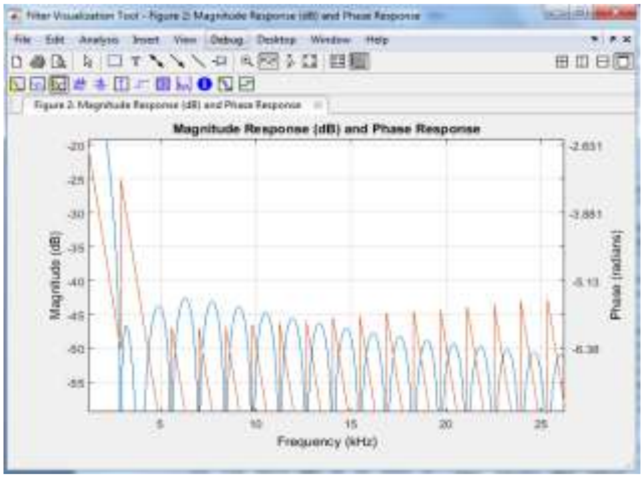

Figure 14: Magnitude response and phase response

The figure 14 is the Magnitude response and phase response. In this figure Magnitude (db) and Phase (radian) is varied with Frequency (KHz). The figure 14 is the magnitude response and Phase response of original and filtered signal. The figure 15 is the Electrocardiogram original and filtered signal. In this signal zero phase response is also displayed. The figure 14 is the magnitude response and phase response. The magnitude of the signal is measured in the form of dB and the phase is measured in the form of radian. The figure 15 is the Electrocardiogram original and filtered signal. Here in this figure original signal, filtered signal and Zero phase filtered with fitfit is displayed. The red line is the zero phase line.

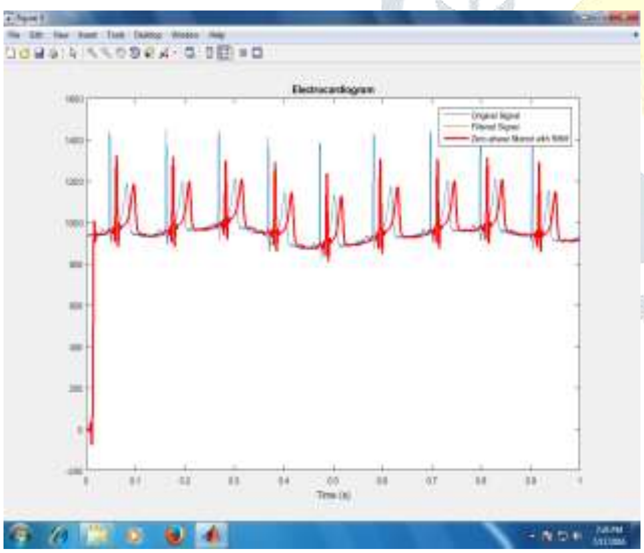

Figure 15: Electrocardiogram

The figure 15 is the Electrocardiogram signal. In this figure filtered and Original Signal is displayed.

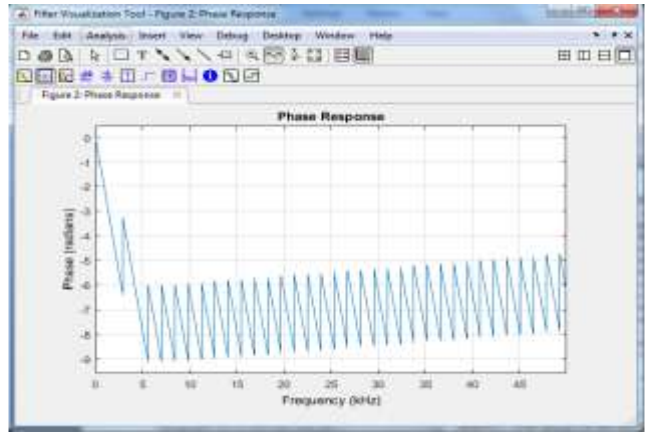

Figure 16: Phase Response

The figure 16 is the Phase response of the signal. In this figure phase (radian) is varied along with the frequency of the signal.

V. CONCLUSION & FUTURE WORK

This paper suggested the use of a multilevel structure for classifying CTS using a deep machine learning method named the DTGNN, in which the input layer by itself develops a level of cyclic learning. This novel fashion of deep learning elaborates the classification performance by exploiting the cyclic contents of the time series, which makes it suitable for the stochastic CTS. In this paper different problems are like specific classification problem, and failed to address a deep learning process for finding the characteristics of the growing scheme. Another problem is temporal and spectral resolution problem. The problem of patient disorder classification and prediction from biological signals. All these problems are resolved with modified Deep Machine Learning Method for Classifying Cyclic Time Series of Biological Signals Using Time-Growing Neural Network. In this work all these problems are resolved with the help of Respiration signals using Deep neural network and in future it is improved with the help of other signals like ECG and EEG signals.

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