Classification of EEG Signals on Standing, Walking and Running Dataset using LSTM-RNN

*K.Murugavalli
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Tamilnadu, India
k.murugavalli@klu.ac.in

Dr. R.Ramalakshmi
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Tamilnadu, India
rama@klu.ac.in

Dr. M.Pallikonda Rajasekaran
Department of Electronics and Communication Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Tamilnadu, India
m.p.raja@klu.ac.in

Dr. Vaibhav Gandhi
Department of Design Engineering and Maths Education
Middlesex University
London
V.Gandhi@mdx.ac.uk

Abstract - **Undoubtedly one of the most important strands of the brain-computer interface (BCI) method is an alternate communication method via brain signals. BCI converts electroencephalogram (EEG) signals from a perception of activity in the brain into user action utilising software and hardware. BCI has piqued the interest of researchers in a wide range of disciplines, such as cognitive science, deep learning, pattern matching, drug treatment medicine, etc. Patients suffering from neuro and cognitive disorders can be assisted through BCI, potentially enabling communication via gestures or just mental imagination. In this paper, a novel combination of Discrete Wavelet Transform (DWT) for extracting the best features and Long Short-Term Memory (LSTM) based Recurrent Neural Network (RNN) is adopted for classifying the EEG signals acquired during standing, walking and running on a treadmill. The dataset used is freely downloaded from Open Science Framework repository. The proposed DWT-LSTMRNN method delivers 96.7% accuracy while classifying four different signals, and thus has the potential to be investigated further on BCI competition datasets that will pave way for a real-time application.**

Keywords-* *Brain Computer Interface (BCI), Electroencephalogram (EEG), Discrete Wavelet Transform (DWT), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN)

I. INTRODUCTION

Brain is a miraculous organ that controls all physical functions, perceives data and represents the significance of the soul and mind. It controls several things, including intellectual ability, innovation, feelings, and memory. The brain, which is secured inside the skull, is made up of the brainstem, cerebrum and cerebellum [1]. Brain illnesses come in numerous forms and the most common types are infectious diseases, stroke, trauma, convulsions, blood vessels, cancers, autoimmune and neurodegenerative conditions [2].

A brain computer interface (BCI) or brain machine interface (BMI) is a device that converts neuronal data into instructions that can control external hardware or software like a computer or automated machines [3]. It enables people to manage machines directly without the physical constrictions of their body. Implanted electrodes may also benefit the patient suffering from stroke, head damages, and Alzheimer's disease. Electroencephalogram (EEG) is a procedure that utilizes small discs like electrodes made up of metal, attached to the scalp to assess the brain's electrical activity. Neurons in the brain interact via electric signals and are constantly active, even while sleeping [4].

BCI with EEG integration aids in evaluating the electrical activity of the brain in healthy, diseased, and epileptic patients [5]. BCI enables patients with motor impairments to control devices and lead normal lives without the need any assistance for basic activities. BCI facilitates them to express their thoughts and feelings through emotion recognition, hand movements, and other means [6]. EEG signals may differ from activity to activity. This study examines the variations in EEG signals acquired while standing, slow walking, fast walking, and running [7]. The most distinguished features from the acquired EEG signals are extracted using the available feature extraction techniques. Feature extraction is a vital part of signal analysis that is essential for system identification, categorization, and acknowledgment [8]. The highly nonlinear method of analysis is applied in many fields to retrieve the nonlinearities of signals. To retrieve relevant features and lessen data dimensionality, deep neural networks (DNN), wavelet scattering, and autoencoders are prevalently utilised [9]. The acquired EEG signals have been transformed to frequency domain utilising DWT in this work, and also aids in the extraction of the best and dominant features present in that signal. After the features have been extracted, they are classified according to their label [10]. The most commonly employed method for data classification is the Artificial Neural Network (ANN). The weights assigned determines the amount of variance between the input and output of ANN [11]. One key constraint of ANN is the selection and adjustment of weights, because smaller weight values result in untrainable models due to weight diffusion, and larger weight values result in poor local minima. To combat this problem and create high-descriptive-ability NNs, a new model of methodologies and algorithms referred as Deep Learning (DL) has been successfully implemented.

Recurrent neural network (RNN) is one among the recent models in DL and have shown better outcomes in wide range of domains, particularly when input and/or output are of different lengths [12]. The RNN network's input lacks data pre - processing, it suffers from gradient vanish and explosion. RNN with LSTM, which fully exploits time-frequency features of signals, has recently emerged as a reliable DL model in a broad range of tasks involving sequence information. The LSTM-RNN cannot just resolve issues in RNN and moreover store long-term data. In this paper, a combination of DWT and LSTM-based RNN is suggested to classify EEG signals gathered during four distinct tasks.

The paper is structured as follows: Detailed introduction about the research and its processes are deliberately explained in Section 1. Section 2 reviews the traditional researchers segmentation methodologies and its outcomes. The description about the dataset utilized in this research is explicated in Section 3. Section 4 elucidates the proposed feature extraction and classification techniques including background works. Section 5 delivers the proposed method implementation process and its results. Section 6 concludes the proposed methods' optimal result.

II. Literature Survey

Tortora et al. suggested a LSTM deep neural network model to decipher the gait phase of 11 healthy people walking on a treadmill using their EEG data [13]. The artifacts associated with movements are eliminated using Reliable Independent Component Analysis (RELICA) and Artifact Subspace Reconstruction (ASR). Using Area-Under-the-Curve metrics, the suggested model successfully reconstructed gait patterns with a robustness of more than 90%. Goh et al. Proposed a model which categorises walking into 4 different categories: free walking, exoskeleton-assisted walking at zero effort, low and high assistive force [14]. Signal artifacts are removed from signals using independent component analysis (ICA). The classification accuracy of Spatio-Spectral Representation Learning, a DNN architecture with shared weights, is 77.8%. Soriano-Segura et al. suggests an innovative strategy focused on event-related desynchronization (ERD) for identifying the intention to alter the direction during gait [15]. EEG signals' temporal and frequency characteristics are extracted and the most significant feature that represent the intention to change direction are separated. The best results come from integrating frequency and temporal characteristics, with an average accuracy of 93.3±11.5%. A multimodel biometric authentication tool called deepkey was created by Zhang et al. using gait and EEG data obtained from inertial measurement unit and Emotiv devices, respectively [16]. It has two parts: an invalid ID screening model to keep out unauthorised subjects and an identification model that employs RNN to simultaneously identify participants by their gait IDs and EEG IDs. DeepKey achieves False Acceptance Rates of 0% and False Rejection Rates of 1.0%.

Cao et al. used the Event-related spectral perturbation (ERSP) approach to analyse the EEG data connected to gait freezing [17]. ERSP is used to analyse the EEG spectra of walking normally, halting voluntarily, freezing of gait (FOG), and transitioning from walking normally to stopping voluntarily and FOG. It is possible to tell the difference between the EEG signal during the shift from walking to deliberate halting and the one during the shift to involuntary stopping brought on by FOG. When compared to FOG episodes, the EEG signature of deliberate halting shows a significantly reduced power spectrum with noticeably altered patterns in the low-beta and delta power in the centre region.

By using EEG signals recorded before the event, Shafiul Hasan et al. explored the potential of a wholly predictive procedure to identify the intention to begin and end a gait cycle [18]. Electrodes were positioned around the sensorimotor cortex to collect EEG data from two amputees and six healthy subjects. The time-frequency domain alpha and beta bands were used to record event-related data using a discrete wavelet transform-based approach. In order to improve classification accuracy, the Hjorth parameters complexity, activity and mobility were obtained as features and the redundant features were removed using a two-sample unpaired Wilcoxon test. A support vector machine (SVM) classifier including an RBF kernel was used to categorise the feature set between the "walk vs. halt" and "rest vs. start" classes using a ten-fold cross-validation procedure. The methodology's overall mean True Positive Rate was 72.06±8.27%, and 1.45 False Positives/min.

Gwin et al. removed gait-related motion noise from EEG data captured during running and walking using a channel-based distortion template regression process and a subsequent spatial filtering strategy [19]. The channel-based noise reduction EEG signals were divided into maximally independent components (ICs) using infomax ICA, and component-based template regression was then carried out.

These results demonstrate that whole-body movements may be studied using high-density EEG, and template regression can be utilised to reduce mechanical artefacts from rhythmic gait events. EMG Removal by Adding Sources of EMG (ERASE), a modified ICA method suggested by Li et al, produces a low false positive rate, good sensitivity, and removes, on average, 26% more EMG artefacts than traditional ICA methodology [20]. These results imply that ERASE may effectively separate EEG signal from EMG artefacts while preserving the underlying EEG properties.

Motion, ocular, and other hindrance movements severely decrease the quality of the EEG signal, causing erroneous results in the measurement of mental workload. A proposed adaptive filter by Rosanne et al., blends traditional approaches with an accelerometer-based reference signal, produces correct results [21]. With ambulant users, a random forest-based mental workload classifier could attain accuracy level up to 95%. The parietal cortex also showed an increase in gamma activity, suggesting a link between sensorimotor integration, workload, and attention among ambulant users.

Traditional researchers investigated the use of NN and DL strategies in collecting and classifying EEG signals for a variety of tasks and produced better results. Despite this, there is room for improvement in terms of classification accuracy, computational cost, and mean squared error (MSE) during training and testing. The notable drawbacks of conventional NN including computational complexity, necessitating more training set, flow of information in one direction and etc. are overwhelmed by the incorporation of RNN. In contrast to a feedforward NN, some layers' outputs are reflected back into the inputs of a preceding layer in RNN. RNNs are distinguished by their capability to handle both past and present input data and to memorise things and were created to address the shortcomings of the feed-forward network. RNN, like ANN and CNN, learns from training data. From then on, it will no longer process information solely on the given input data. Conversely, it makes choices using information from previous inputs. RNN is combined with LSTM for making early prediction in the network. DWT is best suited for analysing non-linear and non-stationary EEG signals, and it is also regarded as a viable approach for representing EEG signal attributes by extracting the features from EEG signal sub-bands. Hence, the proposed combination of DWT and LSTMRNN in this work is novel for classifying EEG signals, and has achieved higher classification accuracy.

III. Dataset Description

The dataset utilized in this study was obtained from the Open Science Framework repository [22]. This research was authorized by Korea University's Institutional Review Board, and all participants provided informed consent in writing prior to the studies. All tests were carried out in compliance with the Helsinki Declaration. The EEG device used has 32 Ag/AgCl electrodes and is attached to the participants' scalp using the 10-20 international system. Two reference electrodes are placed near both the ears. The data was gathered from 10 women and 14 men with an average age of 25. Each participant undergoes and records fifteen trials. In each trial, the subject must complete the following tasks in 100 minutes: standing for the first 25 minutes, slow walking for the next 25 minutes, fast walking for another 25 minutes, and running for the last 25 minutes. Likewise, the trials are repeated for each participant. The participants completed their tasks on a treadmill in the laboratory. The treadmill speed is varied as four different speeds: 0 m/s when standing, 0.8 m/s when slow walking, 1.6 m/s when fast walking, and 2 m/s when running. Participants were given proper rest during and between sessions as required.

The input and the output variables are expressed as X and Y, respectively. The signals acquired for various tasks performed are labelled as follows: [1 0 0 0] represents standing, [1 1 0 0] signifies slow walking, [1 1 1 0] describes fast walking, and [1 1 1 1] indicates running.

IV. Methodology

A. Background Works

1) Feature Extraction: Discrete Wavelet Transform (DWT)

DWT is extensively employed in the process of feature extraction since it works properly in this domain, as evidenced by previous research findings [23]. The feature selection process reduces dimensionality by eliminating redundant features. By implementing DWT, the effectual time-frequency characteristics of every single channel of EEG are retrieved as best features.

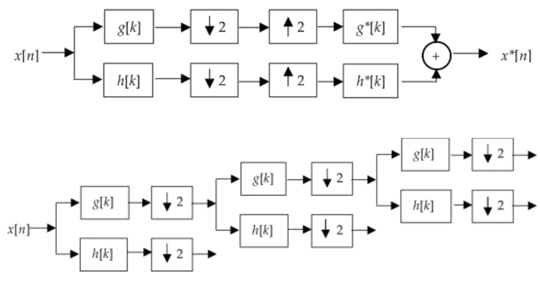

Figure 1. (a) DWT decomposition and recombination (b) WT multiresolution analysis

In this work, db4 (Daubechies) type of wavelet is adopted to extract the features. Whenever the frequency varies greatly in a specific location, it is intricate to extract essential features, whereas the multiresolution approach can break down the lower layer signal to gather additional data. As a result, the decomposed signal can indeed be consistently decomposed to exhibit as much features. The original signal is fed into a low-pass filter g[k] and a high-pass filter h[k] during the wavelet transform. The low-pass filter keeps the original signal's coherence while the high-pass filter keeps the original data's deviation. It has a high frequency resolution and a low temporal resolution in the low-frequency part, but a lower frequency resolution and a higher time resolution in the high-frequency part. Figure 1 (a) depicts the DWT decomposition and recombination, while Figure 1 (b) portrays the WT multiresolution analysis.

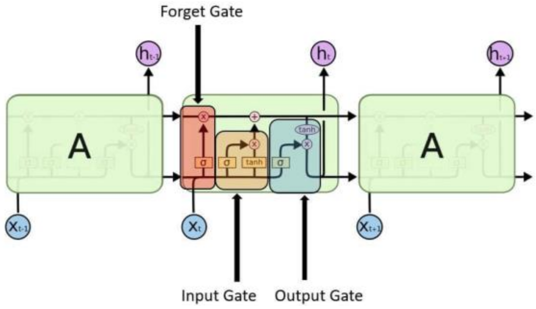

Figure 2. LSTM Architecture

2) Signal Classification: Long Short-Term Memory (LSTM) based Recurrent Neural Network (RNN)

Long-term dependencies can be learned via LSTM-based RNN in the domain of deep learning, particularly in sequence prediction tasks and is depicted in Figure 2. The present RNN step uses the output from the previous step as its input. RNN can predict words based on recent data, but cannot predict words stored in long-term memory. This problem of RNN long-term dependence is solved by LSTM-based RNN [24]. As the gap length increases, RNN's performance is inefficient. By default, the LSTM may hold data for a very long period. It is employed in the processing, prediction, and classification of time-series data. In contrast to typical feed-forward NNs, LSTM has feedback connections. It can manage full data streams in addition to single data pieces. Linked handwriting recognition, unsegmented and speech recognition are the applications for LSTM.

B. Proposed DWT-LSTMRNN Method

The integration of feature extraction and classification technique is employed in this work [25-29]. The low and high pass filters used in DWT are originally used to pre-process the EEG signals obtained while performing various activities on the treadmill. Additionally, it aids in converting the signal's time domain into its frequency domain. From the original EEG data, the widely diverse features are recognised and retrieved. Through the use of the dimensionality reduction technique, DWT aids in the elimination of unnecessary and redundant data. The EEG signal's best features are chosen and retrieved without diluting the signal's originality. The four distinct jobs are each given a unique label. The feature extracted EEG signals are given to LSTMRNN for classifying the different tasks signal. As per the label identity in every moment of the signal, it is classified accurately by means of LSTMRNN. The various steps present in the proposed system is represented in Figure 3.

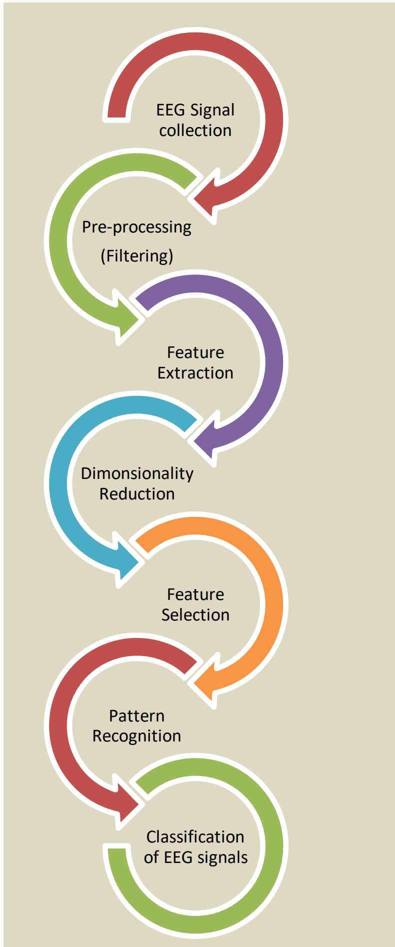

Figure 3. Proposed method workflow

V. Implementation and Results

Initially, the EEG signals collected during four tasks are pre-processed, dimension reduced and then categorized using conventional ANN, yielding the following results during training and testing processes. The four horizontal lines in the Figure 4 (a) represents four different tasks. Here the actual output is denoted as ‘X’ and the network output as ‘O’. The network output ‘O’ in the bottom line represents the non-identified and misclassified values. The values not predicted and categorized under the four tasks by ANN are noticed and grouped collectively in the bottom line. The accuracy attained by the conventional ANN in classifying the tasks is 69.35%.

The regression plot of ANN in classifying the task is portrayed in Figure 4 (b).

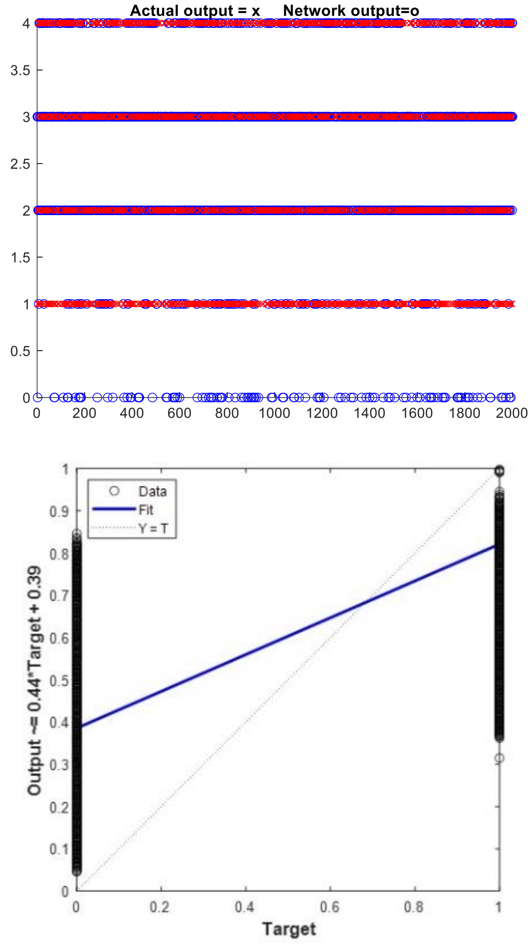

Figure 4. (a) ANN Classification output (b) ANN's regression plot

TABLE I CLASSIFIER TUNING PARAMETERS

Tuning Parameters	ANN	DWT-LSTMRNN
Training samples	4000	4000
Testing samples	2000	2000
No. of Epochs	750	750
Goal	0.01	0.01
Threshold	0.5	0.5

The classification outcomes and the regression plot of DWT-LSTMRNN method is shown in Figure 5. In categorising tasks, the proposed DWT-LSTMRNN accomplishes the classification accuracy of 96.7%. The outcomes indicate that the developed DWT-LSTMRNN method outperforms conventional ANN. The tuning parameters such as the number of training and testing samples, number of epochs, goal and threshold assigned for both the ANN and LSTMRNN classifiers are illustrated in Table I. The outcomes of both the ANN and LSTMRNN classifiers such as Mean squared error (MSE) training, MSE testing, computation time, number of correctly classified data and the classification accuracy are described in Table 2.

TABLE II OUTPUT PARAMETERS OF CONVENTIONAL AND PROPOSED METHOD

Output Parameters	ANN	DWT-LSTMRNN
MSE Training	0.2517	0.1057
Computation Time in Seconds	2.8125	1.9604
MSE Testing	0.2484	0.0922
Number of data correctly classified	1387	1934
Classification accuracy in %	69.35	96.7

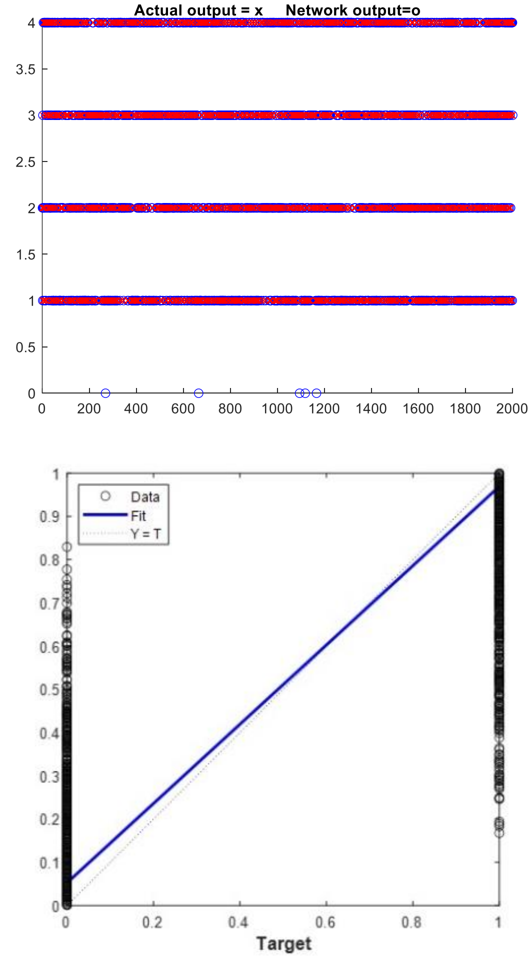

Figure 5. (a) DWT-LSTMRNN Classification output (b) DWT-LSTMRNN's regression plot

VI. Conclusion

BCI can be used as an assistive, rehabilitative, and adaptive technology to observe the brain function and convert certain signal features that represent the person's intent into instructions that control any gadget. People could benefit from BCI systems in a variety of ways, including the ability to manage household appliances, communicate with others while engaging in daily tasks, operate an exoskeleton to enhance the power of the body's joints, or control assistive devices such as a wheelchair or a mobile robot. In this work, for the categorization of four different tasks, the proposed method that combines DWT and LSTM-based RNN is used. The proposed DWT with LSTMRNN method delivers the classification accuracy of 96.7% while conventional DWT with ANN deliver an accuracy of 69.35%. The outcome evidences the incredible work of the suggested innovative combination.

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