Functional Connectivity Evaluation for Infant EEG Signals based on Artificial Neural Network

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***Abstract*—The employment of the brain signals electroencephalography (EEG) could supply a deep intuitive understanding for infants behaviour and their alertness level within the living environment. The study of human brain through a computer-based approach has increased significantly as it aiming at the understanding of infants' mind and measure their attention towards the surrounding activities. The artificial neural network achieved a significant level of success in different fields such as pattern classification, decision making, prediction, and adaptive control by learning from a set of data and construct weight matrices to represent the learning patterns. This research study proposes an artificial neural network based approach to predict the rightward asymmetry or leftward asymmetry which reflects higher frontal functional connectivity in the frontal right and frontal left, respectively within infant's brain. In the traditional methods, the value of asymmetry of the frontal (FA) functional connectivity is used to determine the rightward or the leftward asymmetry. While the proposed approach is trying to predict that without going through all the levels of the calculation complexity. The achieved work will supply a deep understanding into the deployment of the functional connectivity to provide information on the interactions between different brain regions.**

Keywords—Electroencephalography; neural network; EEG signals; infant attention; behaviour; signal features.

I. INTRODUCTION

Human behaviours is visualised in terms of different states; for example; the motor and sensory states, such as eyes movement, lips movement, hand movement, etc. The motor and sensory states are linked with a certain frequency of the signal that helps in the realization the functional behaviour of the infants brain. The major lobes regions in the infants brain include parietal, temporal, frontal, and occipital lobes [1], [2]. The frontal lobe of the infant brain is in charge of the attention, personality, judgment, emotions, and concentration. Therefore, this lobe is an essential piece of the main research works. It is indicated that the parietal and occipital lobes of the infant brain are including the majority of the band power changes occurring in the cognitive activities.

Electroencephalography signal acquisition is the method of recording the electrical activities from the infants brain. This process can be done using a certain number of sensors; the deployed number varies based on the required level of information, placed on the infants scalp. The signals obtained from infants brain are classified based on the frequency as follows: the gamma signal has frequency above 30 Hz, delta signal has less than 4Hz, the alpha signal has 8-13Hz, the theta has frequency of 4-7Hz, and beta has 4-30Hz [1]. Fig. 1 illustrates an example of the Electroencephalography (EEG) waves.

The functional and cognitive behaviour of infants brain can be analysed and understood using EEG. It also can be used to diagnose diseases like coma, encephalopathies, epilepsy, sleep disorders, and brain death. The research works in [3], [4] use EEG signals for cognitive behaviour in an inspiring influence approach. These works has focused in particular on the band power spectrum fluctuation. Power spectrum fluctuation can be related to the alertness. These studies have used the complete frequency spectrum to estimate the fluctuations. The main concentration was based on the response of the auditory, then analysing the required time to press the response button. Such approach could be employed as an acceptable pointer, but in the testing settings, the tested human being will tend to focus and press the button as fast as possible. The results of this study showed that there is a monotonic relationship between the EEG spectrum and minute-scale changes in performance. The work presented in [5] demonstrates that epileptiform discharges in the electroencephalography are an essential element in the diagnosis of epilepsy. Studying the field of epilepsy is quite hard, moreover the detection of epilepsy and the analysis of conventional frequency are not producing successful outcomes. Hence a new approach are used for the classification purposes. This approach has employed a wavelet transform to represent the signal in frequency domain and neural networks and logic regression.

The research work in [6] has used electroencephalography data to measure alertness while doing controlled movements. The cortical activity has been measured in this study by using the amplitude and latency of potentials related to externally cue auditory events. Three different conditions have been used to acquir the data: sitting, cycling and walking. The research work in [7] has employed the data acquired from the eye-movement to draw a conclusion about the alertness level. While The research work in [8], the analysis of video dataset has been deployed for recognizing the behavior. However, the employed dataset was only one-dimensional and there a significant need for a richer dataset from different multiple sources to improve the process of the recognition. Hence, the deployment of electroencephalography dataset supplies a considerable enhancement level for the behaviour analysis and the alertness level.

The functional connectivity (FC) provides information on the reciprocal actions within multiple regions in the human brain [8]. Variety of research papers used different methods of calculating functional connectivity based on their given purpose; however, the general process is that it is done through phase synchronization. This will be discussed in the following section. Phase synchronization can also be known as the phase locking value [9]. Phase synchronization takes EEG two signals/channels and returns a value between 0 and 1 where 0 means no synchronization at all and 1 means full synchronization [8]. Essentially, these values show how well linked is one channel to another. FDSFor applications, it is used for traumatic brain injury, epilepsy, schizophrenia and more [10].

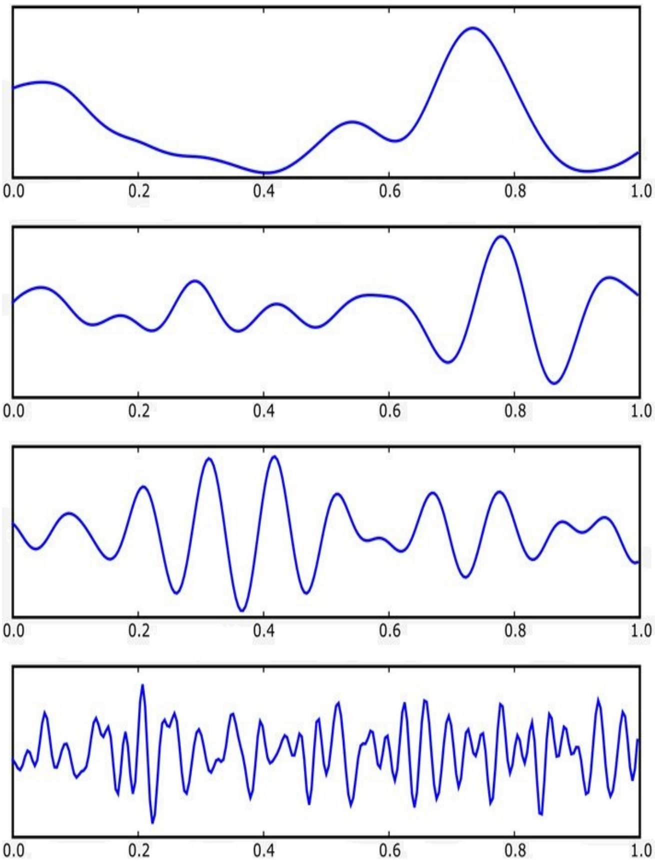

Fig. 1. EEG signals; delta, theta, beta, alpha [1].

The signal power spectrum shows the strength/energy as a function of frequency. The frequencies show where the signal is strong and where it is weak. In computation terms, it is usually done by applying the FFT (Fast Fourier Transform) [11]. Power is used in frequency analysis. The FFT uses the EEG signal/channels and transforms it from the time domain to the frequency domain. Patterns of the signals can be identified by plotting this data, where the frequency is on the x-axis and the voltage/energy is on the y-axis. FFT inspects how closely related the complex EEG signal is to sine waves with frequencies. The more similar the channel is to the sine wave, the higher the absolute value [11]. There are certain frequency bands can be used to extract power to quantify the values: delta (1-4Hz), gamma (30-80Hz), theta (4-8Hz), beta (13-30Hz) alpha (8-13Hz). These frequency bands are linked to specific cognitive states [11]. For example: if there is more power in the theta band in EEG, the patients/participants could be in a state where they have to do many mental calculations/activities. If there is more power in the delta band, the patients/participants could be asleep [11]. EEGLAB [12] or the 'band power' function from MATLAB can be used to calculate the power from these bands [13].

The work presented in this article will contain a group of experiments, which are performed to measure the levels of the distraction of the infants while exposed regularly to certain voices/noises or distractions. The main motivation of the whole research is to build an objectively evaluated whole approach, which has the ability to address the research question of whether an infant can detect a change in a stream of sounds when frequently exposed to changes from standard to deviant. The gained outcome will supply an understanding of the deployment of the functional connectivity to provide information on the interactions between different brain regions. In the traditional method, the value of asymmetry of the frontal (FA) functional connectivity is used to determine the rightward/leftward asymmetry while the proposed approach is trying to predict that without going through all the levels of the calculation complexity. When an infant response to the surrounding changes; this named as a discrepancy reaction. This response was previously suggested to be an indicator for the further language development. Hence, the main aim of the study is to match/analyse the achieved reaction with the continuation for the language level estimation. The employment of the EEG can supply a complete understanding of the infant behaviour and alertness level within the living environment.

This research paper contains the following sections. Section II supply an overview of the related literature review work. While Section III presents the methods, data description and data acquisition. The achieved outcomes and analysis are presented in Section IV and at the end, Section V demonstrates the plan for the future work and the achieved conclusions.

II. Related Literature Review

The relationships between pre- and early post-natal maternal depression and the variations in EEG activity and functional connectivity (FC) in 6 and 18-month old babies are studied in [8]. This research study also looked at externalizing and internalizing behaviours in a 2-year-old child. The samples were enrolled from a longitudinal Singaporean birth group study. Pregnant Asian women were enrolled from the National University Hospital and KK Women's and Children's Hospital from Singapore. The parents were Singapore citizens or from Indian, Malay or Chinese ethnic background. The study used only healthy born infants. It was suggested that infants born to prenatally depressed mothers showed greater right frontal asymmetry in EEG than infants from mothers who are not depressed. Consistent findings have shown that infants of postnatally depressed mothers showed lower left frontal activity in EEG from the ages of 1 month to 3 months, 6 to 13 and 13 to 15 [8], [14].

They measured the brain activity of infants for 40 minutes of an auditory oddball task at 6 months and 18 months of age. Using EEGLAB toolbox, the signals coming from blinking the eyes as well as moving the muscle were removed. The power spectrum was computed of each electrode within the alpha frequency band (6-9 Hz) through employing discrete Fourier transform (FFT in MATLAB) with a Hamming window of 2s period range and 50% overlap between periods. After that, results were log-transformed and averaged through the frontal left (FL) and frontal right (FR) channels. FL channels consist of 12, 19, 20, 23, 24, 26, 27, 28, 33 and 34. FR channels consist of 2, 3, 4, 5, 116, 117, 118, 122, 123 and 124. The greater the power spectrum value shows lower frontal activity. The formula of frontal power asymmetry (FA) was calculated by the following: 2*(FR-FL)/ (FR+FL). The below zero answer from this represents greater relative right frontal activity whereas the positive value represents leftward asymmetry.

They also looked at frontal functional connectivity (FC) which indicates to the connection between separated brain regions and this is calculated by a process called phase synchronization. The process of phase synchronization is explained above. A functional connectivity matrix was computed which consisted of values calculated from phase synchronization. Every row was averaged through each corresponding column, which returned one column. Average functional connectivity was computed through the electrodes at the FL and FR. Frontal functional connectivity asymmetry was computed the same method as frontal power asymmetry.

Individual regression models are employed to assess every measure for the EEG, which includes the frontal power and frontal functional connectivity. Regression analyses took place to investigate the fluctuation of maternal depression with frontal EEG at 6 months of age, as well as, 18 months. Higher postnatal maternal depressive symptoms in comparison to the prenatal ones are related to the higher right frontal activity and right frontal asymmetry at 6 months of age. Conversely, the changes during the maternal depression is not related to the left frontal activity in 6 and 18 months of age, plus, right frontal activity alongside asymmetry at 18 months of age. Higher postnatal maternal depressive symptoms in comparison to the prenatal ones are linked to the (lower, to be specific) right frontal FC in infants of 18 months. In the female experiments, higher postnatal maternal depressive symptoms in comparison to the prenatal ones are strongly linked to higher right frontal activity in the participants who were 6 months of age. This research did not demonstrates any links between prenatal maternal depression with frontal activity in EEG as well as FC at 6 months and at 18 months. They also found out that none of the pre-natal maternal depressive symptoms nor early post-natal maternal depressive symptoms contributed to the prediction of right frontal activity and FC. Asymmetry in 6 and 18 months old infants is also included. Unfortunately, they did not allocate considerable effects of the fluctuation of maternal depressive symptoms about FC in participants of 6 months. In addition, the study did not show any associating of frontal activity in EEG with internalizing and externalizing behaviours. Evidence implies females have higher level of vulnerability to effects of maternal depression than males have. The results show that the symptoms of maternal depression rely on time and it develops over time.

The deep stimulation of brain (DBS) is assessed as an experimental therapy in the areas of treatment-resistant depression as presented in [15]. In this research work, they examined EEG data of 12 patients/participants in resting-state. These patients have experienced DBS surgery. They also linked hemispheric frontal theta and parietal alpha power asymmetry between patients who benefited from DBS and those who did not benefit from it. The study found reliable evidence in neural dynamics due to functional connectivity and EEG power in patients who reacted to DBS as well as patients who did not. The data was filtered so there was no noise. The data was then fast Fourier transformed (FFT in MATLAB) to attain the absolute spectral power in each channel in two frequency bands: theta (4-8 Hz) and alpha (8-12Hz). The frontal power asymmetry measure in the theta band was used in channels F3 and F4. The total difference between frontal theta left-right powers was computed and the total difference of parietal alpha right-left power in order to attain the hemispheric asymmetry.

Phase synchronization was used to calculate functional connectivity. The research work [15] shows the calculation of the computed phase coherence between all pairs of channles and then calculated the average of the synchronization for each channel. Employing this process, they calculated a hemispheric mean synchronization asymmetry. These measures can also be used to analyse network architecture. Data are represented as nodes and edges since the information transfers from one to another. These are shown geometrically in network diagrams [15].

III. Data Gathering and Methodology

A. Data Description

The acquisition of the infant brain electrical activities; EEG, are performed by employing 128 electrodes that represent 128 channels. The place and the digit of all channels are shown in Fig. 2. The gathered unprocessed dataset has gone through the first stage of the analysis, which is filtering the raw data with 0.1-30Hz bandpass. In the second stage; the preprocessed dataset has been segmented into different segments containing 100 ms before stimulus presentation and 1000 ms after according to the category, either "standard" – frequent, repetitive stimulus or "deviant" – infrequently presented different sound. Moreover, artefact has been detected and different data file has been generated. The new file has the information about artefact detected and noise removal. The last stage involved the correction of the data baseline in relation to 100 ms before stimulus onset. All the processed parts are grouped according to the category; 273 standards and 70 deviants, in a text format. This format corresponds to channels in columns from 1 to 128 and 129 is vertex (CZ) and rows correspond to time points, the signal is sampled and extracted each 2 millisecond which makes 550 points/rows.

Firstly, 128 channels have been acquired from the participant, with channels 125-128 recording eye movements.

The age of the infants was between 5 and 7 months. Therefore, the last four channels were not considered in the extraction procedure of the features [8], [14], [15].

The babies are tested with two different voices; the repeated standard and infrequently presented deviant. It was aimed to explore whether the infant can detect a change in a stream of sounds when frequently presented standard changes to deviant or not. When an infant response to the surrounding changes; this named as a discrepancy reaction. This response was previously suggested to be an indicator for the further language development. Hence, the main aim of the study is to match/analyse the achieved reaction with the continuation for the language level estimation. The employment of the EEG can supply a complete understanding of the infant behaviour and alertness level within the living environment.

B. EEG Functional Connectivity

Functional connectivity refers to the combined connection between spatially separated brain regions, which is characterised by level synchronisation of EEG waves of two brain areas in the infant EEG alpha frequency band (6-9 Hz). Phase synchronisation allows functional connectivity to be represented between two brain waves in the alpha frequency of the infant brain.

When we have a signal *s(t)*, with a Hilbert transform $s'(t)$, the instantaneous phase difference $\phi(t)$ between two time series a, b is given by:

$$\Delta\emptyset(t) = \emptyset_a(t) - \emptyset_b(t) = tan^{-1}\left(\frac{S'_a(t)S_b(t) - S_a(t)S'_b(t)}{S_a(t)S_b(t) - S'_a(t)S'_b(t)}\right) \quad (1)$$

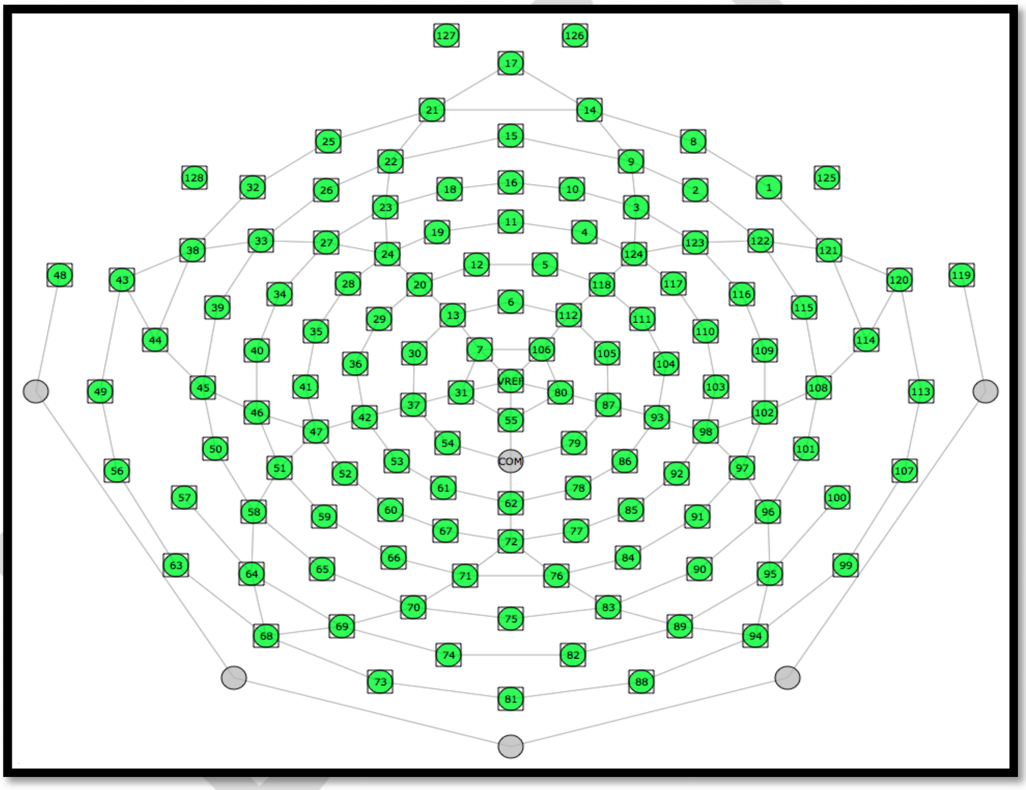

Fig. 2. The Electroencephalography electrodes map – where some electrodes form the frontal left area of the brain and others form the frontal right area.

While the mean phase coherency measure of synchronization can be given as:

$$R = \left| \frac{1}{N} \sum_{J}^{N-1} e^{i\Delta\emptyset(j\Delta t)} \right| \quad (2)$$

In this equation, N refers to the total sample number. Mean phase coherency takes on values between 0 and 1. Where 0 = no synchronisation, 1 = full synchronisation between two signals. The mean synchronization S_j^{mean} for each electrode can be calculated using the following equation, where, S_{ij} is the phase coherence, between all pairs of electrodes:

$$S_j^{mean} = \frac{1}{N} \sum_{i=1, i\neq j}^{N} S_{ij} \quad (3)$$

Where, N refers to the number of electrodes.

C. *Artificial Neural Networks*

The artificial neural network (ANN) is one of the artificial intelligence techniques with the capability to learn from a set of data and construct weight matrices to represent the learning patterns. The artificial neural network has had great success in many applications including pattern classification, decision making, forecasting, and adaptive control.

Artificial neural networks has shown a significant level of success. It has been deployed in many research works in different fields. The research work presented in [16] shows different classifications methods used to predict heart disease risk level in patients based on blood pressure, gender, age based on artificial neural networks, Naïve Bayes, KNN, decision tree. Artificial neural networks are a mathematical or a computational model designed for the simulating the biological neural activities (in the brain) similar to the model proposed in [17]. This model is composed of three layers; the input layer, hidden and output layers. The inputs go through the input layer and processed through the hidden layer until a result is obtained through the output layer. The actual output is then compared to the expected output. An artificial neural network based on backpropagation is useful for the classification problems and it is a suitable and effective technique [18].

The artificial neural network has been trained using a Levenberg-Marquardt backpropagation training algorithm as discussed in the coming section. This approach is using a combination of techniques including gradient descent approach, and Gauss-Newton technique which allows the artificial neural network to be trained effectively [19]. The proposed artificial neural network has used a hyperbolic tangent sigmoid activation function within its layers. Fig. 3 shows the tangent-sigmoid activation functions, where *n* is the input.

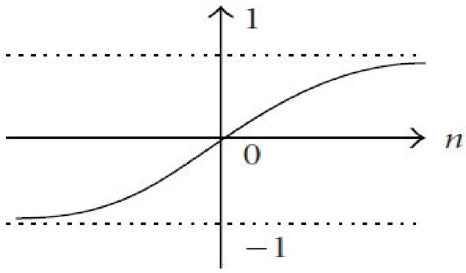

Fig. 3. The tangent-sigmoid activation function of the proposed artificial neural network.

IV. RESULTS AND DISCUSSION

The functional connectivity has been calculated for all the participant infants. The acquired raw data from each infant has been filtered with 0.1-30Hz band pass. Afterwards; the generated data is divided into different parts containing 100 ms before stimulus presentation and 1000 ms after according to the category, either “standard” – frequent, repetitive stimulus or “deviant” – infrequently presented different sound. Once this step has been completed, the artefact is detected and a new file is generated which involves the information about detected artefact and deleted noise. At the end, the basement of the dataset is modified within the range 100 ms.

The initial results have been generated based on the calculation of phase synchronisation. The phase synchronisation can be used to represent the functional connectivity among the pair of the EEG channels. The value of the phase synchronization varies between zero and one. Where zero refers to the absence of synchronization; and one refers to the full synchronization among the pair of signals in question. After calculating the phase synchronisation a matrix (G) has been generated; this matrix refers to te functional connectivity of the signals; where each element of this matrix (G_{ij}) is a phase synchronisation between the i^{th} and j^{th} channels in the processed data. After creating this matrix, the functional connectivity of the i^{th} channel has been calculated by taking the averaging G_{ij} over all the column j. The last step involves calculating the average functional connectivity from the signals in the frontal left area (FL) and the frontal right (FR) area. The frontal left (FL) area contains the following channels 12, 19, 20, 23, 24, 26, 27, 28, 33 and 34. The frontal right (FR) area contains 2, 3, 4, 5, 116, 117, 118, 122, 123 and 124. After generating the frontal left and the frontal right areas, the frontal power asymmetry (FA) has been calculated as follows:

$$FA = \frac{2(\mathrm{FR} - \mathrm{FL})}{(\mathrm{FR} + \mathrm{FL})} \quad (4)$$

Fig. 4 shows the EEG functional connectivity for two infants (P11 and P23) over all the main 124 EEG channels, where a synchronisation can be seen between the two graphs at different values. Although the functional connectivity values are different between the two presented examples, there is a clear synchronization between the corresponding channels starting from channel one until the end of the channels of the participants.

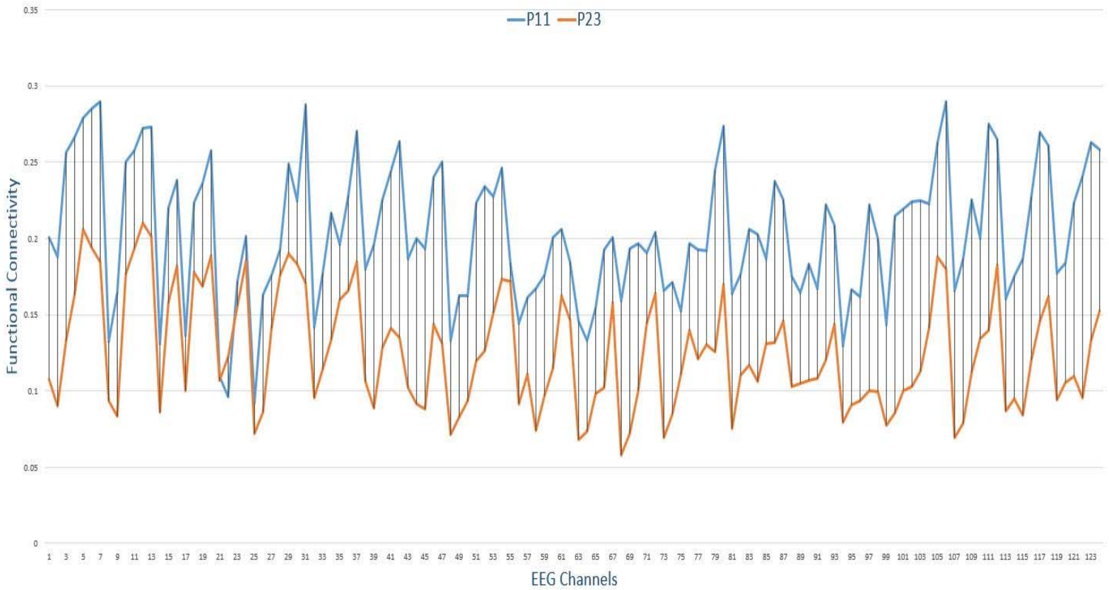

Fig. 4. EEG functional connectivity for two infants (P11 and P23) over all the main 124 EEG channels, where a synchronisation can be seen between the two graphs at different values.

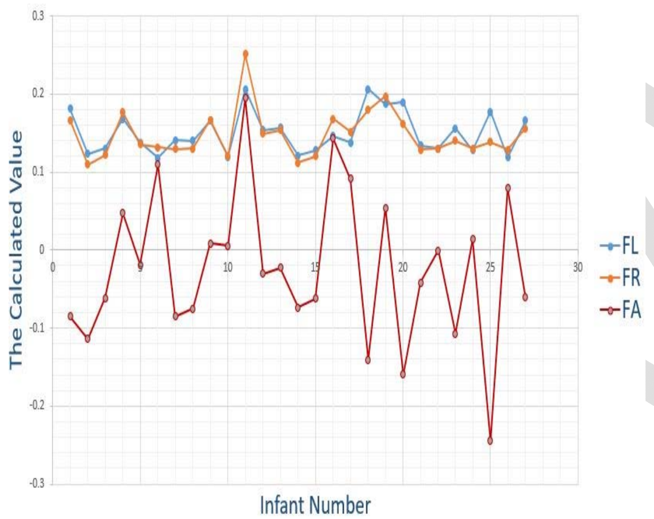

Fig. 5. EEG frontal left (FL), frontal right (FR) and frontal asymmetry (FA) for all the participating infants based on the deviant signals.

Fig. 5 shows the EEG frontal left (FL), frontal right (FR) and frontal asymmetry for the entire participant infants based on the deviant signals. It is clear from the graph that infants 1, 2, 3, 5, 7, 8, 12, 13, 14, 15, 18, 20, 21, 22, 23, 25, and 27 have a negative frontal asymmetry values. While infants 4, 6, 9, 10, 11, 16, 17, 19, 24 and 26 have a positive frontal asymmetry values.

The developed artificial neural network has been used and tested using the available dataset for a different number of infants. The artificial neural network is used to identify whether the participant has frontal asymmetry towards the left or the right. The available data set have been divided into a 70% of training set, 15% of a testing set, and 15% of validation set. The dataset part used for training is effectively trained through the employment of Levenberg-Marquardt backpropagation training approach. The proposed method deploys a combination of approaches including gradient descent approach, and Gauss-Newton technique which allows the artificial neural network to be trained effectively [19]. The ANN is trained through the following approaches to make sure the best outcomes and performance of the artificial neural network are achieved. These approaches include gradient descent with momentum backpropagation [20,21], gradient descent with adaptive learning rate backpropagation [22]. After performing the training using the three approaches a comparison has been carried out to identify and select the best one. The best performance was achieved using Levenberg-Marquardt backpropagation training approach. This approach is employing a mixture of techniques which allows the artificial neural network to be trained in an effective manner. This mixture of techniques includes backpropagation, gradient descent approach, and Gauss-Newton technique [23,24].

The selected trained artificial NN is evaluated completely. The achieved result is good, wherease the confusion matrix demonstartes that there are five negative cases classified as positive, and 4 positive cases have been misclassified as negative cases. The total accuracy is 67%. Where, the accuracy Acc is calculated as follows:

Acc= true positive + true negative / all outputs. (5)

The misclassification rate (MSR) is 0.33 and can calculted as follows:

Misclassification rate = false positive + false negative / all outputs.

The details of the confusion matrix are as follows:

- False negative rate = false negatives / all output negatives.
- False positive rate = false positives / all output positives.

- True positive rate = true positives / all output positives.
- True negative rate = true negatives / all output negatives.

The false negative rate is 0.2353, the false positive rate is 0.5, the true positive rate is 0.6, and the true negative rate is 0.4444. The trained network has achieved an accuracy of 67%, which is reasonable enough based on the available data sets. Therefore, more data sets will be collected and embedded in the system to allow the network to be trained on a wider range of data sets, which represent a wider variety of participants. The collected data sets will go through the preprocessing stage, which includes off-line filtering with a band pass 0.1-30 HZ filter, segmenting into epochs time-locked to stimulus onset. Afterward, the data sets will be divided into a training set; 70%, a testing set; 15%, and a validation set; 15%. To perform further analysis on the acquired data sets, a group of statistical features will be extracted from each dataset and link it with the status of the participants. The final features involve: kurtosis, energy, standard deviation, mean, and skewness,. The different surrounding environment will be considered (different tones) while recording the EEG signals as a response to these standards and infrequently presented different tones.

V. CONCLUSION

The proposed study presented an artificial neural network based method to predict the rightward asymmetry or leftward asymmetry which reflects a higher frontal functional connectivity in the frontal right and frontal left respectively in the infant's brain. In the traditional method, the value of asymmetry of the frontal (FA) functional connectivity is used to determine the rightward/leftward asymmetry. While the proposed approach is trying to predict that without going through all the level of the calculation complexity of the traditional approaches. The achieved work aims to provide an insight into the deployment of the functional connectivity to provide information on the interactions between different brain regions. The employment of electroencephalography (EEG) can supply a full understanding of the infants behaviour and alertness level within the living environment. The study of human brain through a computer-based approach has increased significantly as it aiming at the understanding of infants' mind and measure their attention towards the surrounding activities. The trained network has achieved a reasonable accuracy, which is adequate based on the available data sets. Therefore, more data sets will be collected and embedded in the developed system to allow the neural network to be trained on a wider range of data sets which represent a wider variety of the infant participants.

The future work of the proposed work will look at a wider series of the experiments, which are performed to measure the levels of confusion of the infants while exposed frequently to some specific sounds or distractions within a different environment. The main motivation of the whole research is to build an objectively evaluated the whole approach, which has the ability to meet the research question of whether the infants has the ability to detect a change in a stream of sounds when frequently presented standard changes to deviant. The response to such environment can be suggested to be a predictor of further language development for the participant. The employment of electroencephalography (EEG) can supply a full understanding of the infants behaviour and alertness level within the living environment. The obtained infants EEG datasets will be evaluated to construct an objectively analysed model that has the ability to give an automatic insight of the infants' behavior. This can fully underpin the infant specialists in analyzing the infant attention for stimuli in the surrounding environments.

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