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Parents' mHealth App for promoting early dyslexia biomarker detection in children at home or kindergarten: Feasibility, Acceptability, Economic impact and Pilot Study and Survey Results

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Abstract

The use of mobile apps in diagnosing and improving health conditions has increased in recent years. If dyslexia isdiagnosed between 3 to 6 years old, dyslexic children's lives should evolve in a better way. With the right intervention methods, dyslexic children may not be diagnosed with dyslexia when they go to school at the age of 7. Therefore, dyslexia diagnosis at an early age is very important but mostly delayed until the age of 8 officially to give a chance to overcome any maturation delays. In the literature, there is no clinically-tested mobile app for dyslexia biomarker detection that can objectively assess and monitor the child's situation at home or in kindergarten. Many different dyslexia biomarker detection methods exist in the literature. These methods are based on questionnaires, MRI scans, PET scans, EEG scans, and eye-tracking scans using Machine Learning methods. Each of these methods has its own drawbacks, such as the psychometric tests taking more than 1 hour, or MRI scans and eye tracking solutions being expensive and being difficult to collect data – and the results may not be accurate enough to generalize as dyslexia have many subtypes. Here we present a novel mobile app that has an embedded dyslexia biomarker based on Z-scored QEEG data that has accomplished a high accuracy rate in diagnosing dyslexia. The mobile app can be used at home by parents or teachers in kindergarten. We have collected data from 207 children (96 of them have dyslexia, 111 of them are typically developing) between 7-10 years old for 60 sessions. The data consists of the eyes-open resting state 2-minute QEEG data from 14-channels. In order to standardize the data, the Z-scores are calculated. Using the ANN machine learning method, dyslexic/normal classification has been done with a high accuracy rate (98.8%). ANN yields the highest accuracy results with standardized QEEG data in the literature. Auto Train Brain is a novel mobile app that has dyslexia biomarker detection software embedded into it. A survey is created to assess the mobile app's dyslexia biomarker detection module's feasibility, acceptability, and economic impact. The results have shown that the app module is found feasible and acceptable by families, however, it is found expensive to use at home.

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1. Introduction

Dyslexia is a type of learning problem that has neurological underpinnings. It's characterized by problems with accurate and fluent word recognition, as well as poor spelling skills. Although IQ is normal or above normal, dyslexic people find it difficult to read. Other dyslexia-related implications include difficulties with reading comprehension and a lack of reading experience, both of which can hinder the development of vocabulary and knowledge (Lyon, Shaywitz, & B.A. Shaywitz, 2003). Because of weak connections, there is a "disconnection hypothesis" for dyslexia (Paulesu et al., 1996).

Reading is an acquired ability for humans. A child's visual and auditory abilities should be developed as time goes by and the left hemispheric lateralization should be completed by the age of 7 before the child starts school and learns how to read. Before the diagnosis of dyslexia, additional learning support should be provided to the child and the nutritional deficiencies should be eliminated. The diagnosis of dyslexia is performed by psychiatrists; they use psychometric tests, and the first diagnosis may start 2 years after the child starts school. During this period, as the child cannot properly read and write, his self-esteem would go down and his academic life would start to be affected by the late intervention. With the help of computers and machine learning, this period would be shortened, and the diagnosis of dyslexia could be done even before the child starts school from 3-to 7 years old, and the remedial interventions may be taken much beforehand. Therefore, some children may overcome dyslexia even before they start reading.

In the literature, machine learning methods have been utilized to diagnose dyslexia. These algorithms use psychometric test results, fMRI scans, EEG scans, PET scans, MEG scans, eye tracking information, face images, handwritten texts, and mobile-based games. Psychometric tests take 1.5- 2 hours, and the child should be taken to a psychiatrist. Wechsler Abbreviated Scale of Intelligence (WASI, II, III&IV) (Wechsler, 1999), Wide Range Achievement Test: Revision R,3&4 (WRAT-R,3&4) (Jastak & Wilkinson, 1984), Woodcock & Johnson III (WJ-III) (Schrank, 2011), Comprehensive Test of Phonological Processing (CTOPP) (Wagner et al.,1999), and Peabody Picture Vocabulary Test: Third Edition (PPVT-III) (Dunn & Dunn, 1965), Test of integrated language and literacy skills (TILLS test) (Nelson et al., 2016), and WISC-R tests (Kaufman, 1994) are used as psychometric tests. Visiting a psychiatrist could be a horrifying experience for a 7-year-old child, as dyslexia is not classified as a mental disease; instead, it is solved with rehabilitation and special education after the diagnosis. Although fMRI scans and eye tracking data yield high-accuracy results compared with other methods, they are expensive solutions. It is hard to use MRI scans and eye tracking methods to collect data from a 7-year-old child as they require expensive equipment. Collecting face images from children brings privacy and security issues for the child and their families. The algorithms that use EEG scans, despite being a cheaper way to collect data, do not yield a high accuracy result to go to the market in the literature.

On EEG scan data sets, Al-Barhamtoshy and Motaweh (2017) used K-means, ANN, and fuzzy logic classifiers to reach an accuracy of 89.6%, 89.6%, and 85.7 percent, respectively. The three models were shown to have an overall accuracy of 81.1%, 62% precision, 100% recall, and 76.6% F-score. Karim et al. (2013) employed a Multilayer Perceptron to detect dyslexia signs by collecting brain waves in the resting state. With eyes closed, the accuracy was 85%, and with eyes open, it was 86%. Using machine learning, Frid and Breznitz (2018) investigated the variations in ERP signals between dyslexic and proficient readers. They used SVM, ANN, and PCA to get a 78% accuracy. In the literature, the best accuracy scores reached with ANN on fMRI scans and DTI scans are 94.8% (Chimeno et al.,2014).
The best accuracy results with eye tracker data were 95.6% with SVM- RFE (Benfatto et al., 2016). The best accuracy result for dyslexia detection with handwriting data was 77.6% (Spoon et al.,2019). The best accuracy results with psychometric test scores were 99% (Khan et al., 2018).

We wanted to see if we could accurately diagnose dyslexia using z-scored QEEG recordings from 14-channel band power data (greater than 95 percent). This is the first study that used ANN to classify the Z-scores collected from QEEG data of children with dyslexia, and it achieved a 99.8% accuracy rate; the mobile app that includes the dyslexia biomarker detection is reachable by families and can be used at home.

Auto Train Brain is a mobile app with a headset that improves the cognitive abilities of dyslexia. The efficacy was proven with a clinical trial beforehand a clinical trial and it was shown that using Auto Train Brain improves reading comprehension and reading speed (Eroğlu et al., 2020).

2. Methods and materials

2.1. Participants

96 children with pure dyslexia (M_{age}= 8.85, *SD* = 1.56; 70 males, 20 females; the ethnic group is white) who used Auto Train Brain at home on a regular basis for neurofeedback formed our experiment group. There were 111 children in the control group who were developing typically (M_{age}= 8.80, *SD* = 1.60; 80 males, 31 females; the ethnic group is white). Psychiatrists identified the children in the experimental group with dyslexia, and their doctors advised their families to utilize Auto Train Brain at home. The subjects satisfied the DSM-V dyslexia criteria, as determined by psychologists and psychiatrists using the TILLS tests. These children were picked at random to take part in the experiment. The study is designed as a retrospective, the participant's main aim is to use Auto Train Brain software as a neurofeedback device at home. The task they were assigned was a resting state 2-minute EEG measurement before each neurofeedback session for collecting data. The participants used Auto Train Brain in the mornings before school. The study's inclusion criteria were that the participants did not use any medicines and did not have any other comorbid disorders than dyslexia and they came from middle-SES families. They lived in many cities around Turkey. A poll of the children's parents was used to assess their socioeconomic condition. Questions regarding education (primary school, high school, university), income (basic income 6,000 TL, mid-level income 6,000 TL to 20,000 TL, high income>20,000 TL), and occupation are included

in the survey (staff, blue-collar workers, white-collar workers).

Before each neurofeedback session, 2-minute resting-state eyes-open theta, alpha, beta1, beta2, and gamma-band powers were obtained (60 sessions per subject on average). This is a small sample size research with repeated measurements (12,420 sessions and 207 participants). The 2-minute resting-state eyes open QEEG data from the typically developing children are collected with Auto Train Brain and the experimental and the control group data is balanced to have an equal number of cases in each group.

2.2. Electroencephalography (EEG) recording

The EPOC+ and EPOC-X headsets from EMOTIV were utilized throughout the tests. The headset's internal sampling rate was 2048 samples per second per channel. The EEG data were filtered to eliminate primary artifacts and alias frequencies before being down-sampled to 128 per second per channel. There were 14 EEG channels plus two controls, with each channel receiving 128 samples per second. Before the training, EMOTIV APP mobile applications were used to calibrate the EMOTIV EPOC+ headset on the participants' scalps, ensuring that each electrode was capable of transmitting high-quality EEG data. All 14-channel EEG data was captured during the tests in theta (4-8 Hz), alpha (8-12 Hz), beta-1 (12-16 Hz), beta-2 (16-25 Hz), and gamma (25-45 Hz) bands for all analyses in this work. In EMOTIV headset interfaces, delta (0-4 Hz) band data was not present. EMOTIV EPOC+ has been shown to deliver research-grade QEEG data (Badcock et al, 2013). There are 70 features in the dataset with information of a person whether the patient is dyslexic or not. The data is collected from electrodes located on the Auto Brain Train product (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4). The features are labeled according to the position of the electrodes. The readings of the product contain theta, alpha, beta, and gamma frequencies of brain activity in specific locations.

2.3. Neurofeedback treatment protocol and multi-sensory learning method

Auto Train Brain is a smartphone software that employs neurofeedback and multisensory learning techniques. It's compatible with the EPOC+ and EPOC-X headsets from EMOTIV. It's a non-invasive approach that helps adults and children enhance their brain performance over time. Only a brief headache has been recorded as a side effect on a few occasions. Traditional neurofeedback training may have unintended consequences if it is used on the wrong parts of the brain or if improper neurofeedback protocols are used for the subject's condition. Before each neurofeedback session, Auto Train Brain's AI-assisted algorithms examine the 2-minute resting state eyes-open QEEG data and, depending on the findings, offer the most appropriate neurofeedback protocol for the next session. Auto Train Brain has collected norm data from 1700 healthy persons ranging in age from 4 to 80. During the neurofeedback session, this norm data is utilized to compare the subject's QEEG values to those of normal persons. The most abnormal brain areas are subjected to neurofeedback training. Auto Train Brain was created with the goal of reducing negative effects and has been shown to be beneficial in earlier research and clinical trials for children (Eroğlu et al., 2021). It reads and interprets QEEG signals from 14 channels and delivers online, real-time visual and aural neurofeedback. A system and method for boosting learning capacity are offered inside this software program. Dyslexia is described in the literature as a disconnection condition in the left temporal area, thus we thought the following approach might be useful. This neurofeedback approach was previously tested on dyslexic children and patented (Eroğlu et al.,2021).

- Reduce absolute theta waves at FC5 if they are higher than the age-matched norm theta; and/or,
- Reduce absolute theta waves at T7- P7- O1 if they are higher than the age-matched norm theta; and/or,
- Find the channels with the highest absolute power of theta waves in the left hemisphere and reduce absolute theta; and/or,
- Find the channels with the highest absolute power of theta waves in the right hemisphere and reduce absolute theta.

A green arrow on the screen indicates a good reward, whereas a red arrow and a "beep" sound indicate negative feedback. The score displayed on the screen rises when a favorable reward is received. A red arrow is displayed on the screen if the person's slow brain waves are over the norm absolute theta, and the participant is instructed to try to transform it into a green arrow. A 30-minute neurofeedback session is common. A phoneme-grapheme matching alphabet teaching method is offered after the neurofeedback session. One of the key distinctions between the Auto Train Brain and other neurofeedback systems is that it integrates neurofeedback with multi-sensory learning concepts. The 14-channel neurofeedback methodology is also unique. As described by Eroğlu et al. (2021), lowering theta using Auto Train Brain reduces the disconnection syndrome in dyslexia. Theoretically, Auto Train Brain reduces the disconnection syndrome between the Broca and Wernicke regions by lowering theta in the temporal region and/or the left hemisphere. Coherence across various brain areas is practically enhanced by lowering QEEG theta band power, as evidenced by the TILLS test findings.

2.4. Study Design

The Auto Train Brain solution is a mobile app that may be used at home. Each participant sat on a chair while the electrodes were inserted for the QEEG assessment. The distance between the participant and the mobile phone screen was 0.5 meters. The QEEG measurements were taken for 2 minutes before each neurofeedback session using the EMOTIV EPOC+ or EPOC-X and the Auto Train Brain app. The participant was requested to complete the QEEG measurement while relaxing and with their eyes open. This study is designed as a repeated measurement with a small sample size.

The survey to assess the app's feasibility and acceptance by the users consists of 6 questions: (1) Is the diagnosis shown on the mobile app correspond to that of the psychiatrists? (2) Is it easier to use the app on a child (3) Do you suggest this app to any other people? (4) Would you prefer to use this app for dyslexia classification at home or in kindergarten? (5) Do you think the price of acquiring the solution (EEG headset and software subscription) is high/ moderate/ low for neurofeedback and dyslexia/normal classification purposes? (6) Do you think the price of 1-time measurement (dyslexia/normal classification) in a kindergarten is high/ moderate /low? 41 people participated in the survey. These are middle-aged parents (35- 45 years old, 60% female, 40% male). The socioeconomic situation of the parents was middle class. The parents have used the Auto Train Brain solution at home beforehand.

2.5. Statistical Analysis

Python/Google Collab, Sci-kit Learn, and TensorFlow ML libraries were used to conduct the statistical and data analysis. K-Folding, Cross-validation, and confusion matrix generator functions derived from ML libraries. Mat plot library stands for plotting learning, validation, and ROC curves. The averaged 2-minute QEEG band power data (continuous data) are acquired from fourteen electrode channels each session. For the whole data set, the Z-scores are computed using the equation $z = (x-m)/s$ for each QEEG band power (including the experiment and the control group). Because EMOTIV does not offer Z-scores, m and s stand for the sample's mean and sample standard deviation, respectively. Outliers (>5 or -5) were removed from the analysis. The missing values were replaced with the mean of the featured data. The data is labeled by a computer scientist following the psychiatrist's diagnosis of the participant. The diagnosis of the participant has not changed across neurofeedback sessions although there may be some improvements in the brain signals. The dyslexic and healthy participants' data were balanced with pre-processing operations and adjustments. The binary classification with a supervised ML model is applied. The model output is the dyslexia positivity probability score. The ML model architecture is Artificial Neural Network. The model features made in the study are epoch 60, batch size 32, and loss as binary cross-entropy. The k-fold cross-validation technique has been used to evaluate the model with ten-folded cross-validation. This method is generally used to test model performance to estimate how well the model performs on unseen data. The overfitting is prevented by applying the dropout between layers. The results have been tested with an external test set which contains a diverse set of input data.

3. Results

In this research, we have designed a Machine Learning algorithm to classify dyslexia and assessed the effectiveness with a survey. This study is a repeated measurement (12,420 sessions) with a small sample size (207 participants: 96 of them have dyslexia, and 111 of them are typically developing).

The artificial neural networks achieved high accuracy and low-loss functions. The results show the performance of suggested preprocessing methods and the artificial neural network models achieved 98.8% accuracy with 0.05 loss with a 95% of confidence interval (CI, k-fold cross-validation applied), which is the state-of-the-art in literature for dyslexia biomarker detection with EEG scans. In addition to that, this study concludes models which have additional preprocessing techniques like minimum-maximum scaler, standard scaler, etc. reduced the accuracy slightly from 98.8% to 98.63%. F1 score and loss become 0.986 and 0.07 respectively.

Table 1. Top 3 ANN results on the data set to detect the dyslexia biomarkers.

Model Architecture	Accuracy	F1	Loss	AUC
1st tanh , 2ndsoftsign, 3rd tanh , 4thsigmoid,	**0.98807**	**0.9881**	**0.05**	**0.98**
min max Scaler + 1st *tanh* , 2nd*softsign* 3rd *tanh* , 4th*sigmoid*	0.9863	0.986	0.07	0.96
1st *tanh* , 2nd*softsign* 3rd *tanh* , 4th*sigmoid*	0.9818	0.982	0.09	0.95

In Table 1, model architecture talks about ANN architecture of every individual activation function in the system. Even though this study achieves high-accuracy results, it is also important to examine the cases of people who were misclassified by the model. According to the confusion matrix in Figure 2, the model claims 72 non-dyslexic people as dyslexic. On the other hand, the model states that 27 dyslexic people as non-dyslexic out of 8301 samples. In this study, the number of false negatives is more important than the number of false positives. Although, misclassifying non-dyslexic people as dyslexic -false positives- would not create problems when it comes to the neurofeedback system of Auto Brain Train, but it is essential to consider dyslexic people classified as non-dyslexic -false negative- predictions.

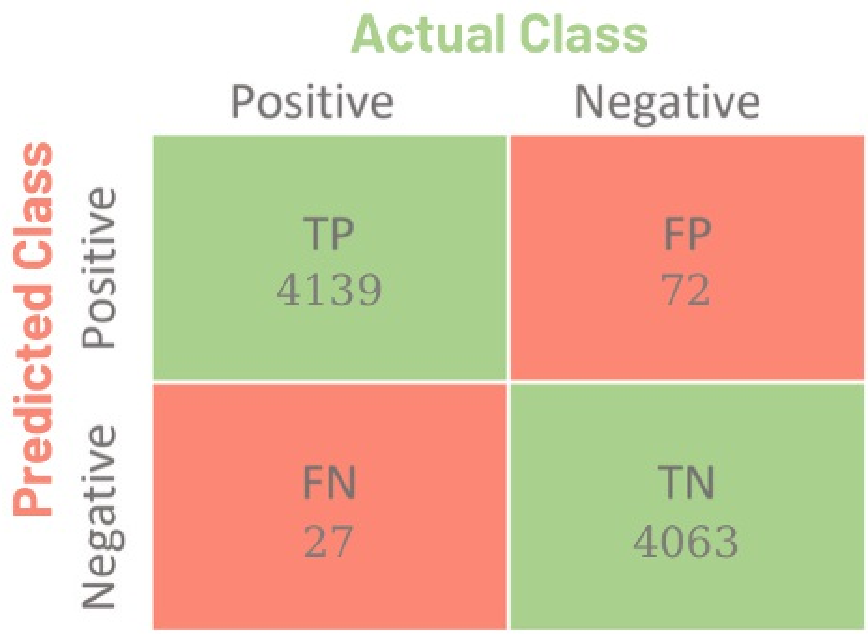

Figure 2. *Confusion matrix result of the best model*

The receiver Operating Characteristic (ROC) Curve, which stands for sensitivity and specificity, of the ANN model indicates the capability of the model to discriminate dyslexia and the results were very promising (Figure 3). This study achieved a 0.98 area under curve (AUC) score. According to the ROC Curve definition, an AUC value between 0.8 and 0.9 is considered excellent, and more than 0.9 is outstanding.

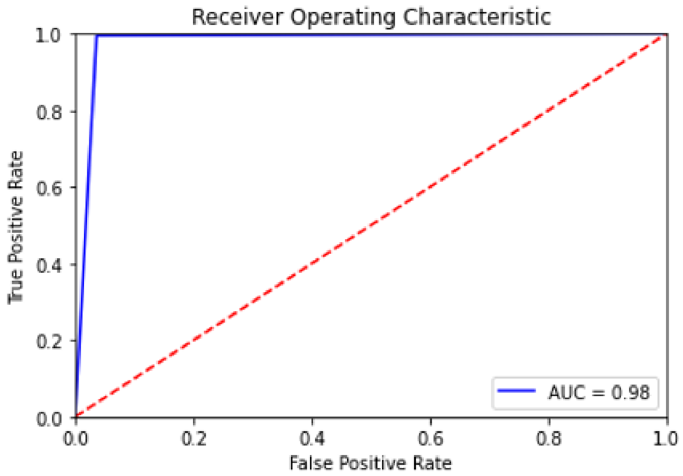

Figure 3. *Receiver Operating Characteristic Curve*

The survey results (N= 41) indicate that 99% of the respondents found the results of the diagnosis correspond to that of the psychiatrists; 92% of the respondents find the app easily usable at home; 82.9% of the respondents suggest the other users use the app. 50% of the respondents prefer to use the app for dyslexia/normal classification in kindergarten. 75% of the respondents find the total cost of ownership (the price of the EEG headset and the software subscription) high for usage at home. 78% of the respondents think the price of the one-time measurement (dyslexia/normal classification) in kindergarten is moderate.

4. Discussion

The novelty of this research is that Z-score normalization of 14- channel QEEG data has led the high-accuracy results and the ML model is embedded into Auto Train Brain mobile app for everyday usage. The feasibility, acceptability, and economic impact of the mobile app are assessed with a survey in the real life afterward.

This is the first research in the literature where ANN yields high accuracy results (98.88%) with z-scored QEEG data for dyslexia biomarker detection. An artificial neural network (ANN) is a non-parametric machine learning which does not assume anything about the data set, it is focused on finding the discriminant function to diagnose dyslexia. As we collect QEEG data from 14 channels, it is expected that data may be correlated, and the covariance matrix is not diagonal. ANN still performs well under these conditions with QEEG data. We have standardized the data with Z-score calculation and eliminated the outliers. We have also balanced the data sets of the experimental and the control group. Eliminating the noise and outliers in the data helped to achieve such a high accuracy.

On EEG scan data sets, Al-Barhamtoshy and Motaweh (2017) used ANN (89.6% percent accuracy). Karim et al. (2013) employed a Multilayer Perceptron to detect dyslexia signs by collecting brain waves in the resting state (85% accuracy). Using machine learning, Frid and Breznitz (2018) investigated the variations in ERP signals between dyslexic and proficient readers (with ANN, 78% accuracy). O. L. Usman et al. (2020) achieved state-of-the-art CNN architecture with MRI scans at 84.6%.

Our research with QEEG data with ANN yielded 98.8% accuracy which is the highest accuracy in the literature with K-fold cross-validation. An idea that can also achieve better results is to try different types of artificial neural network models such as generative-adversarial networks, convolutional neural networks, and recurrent neural networks.

The machine learning model created with ANN is converted to a TFLITE model and embedded into the Android Mobile Application of Auto Train Brain on Android and iOS (Figure 4). In this way, the diagnosis of dyslexia with a high accuracy rate becomes possible with 2-minute resting-state QEEG data collected from Auto Train Brain (Figure 5, figure 6).

Figure 4. *A dyslexic child who uses Auto Train Brain mHealth app*

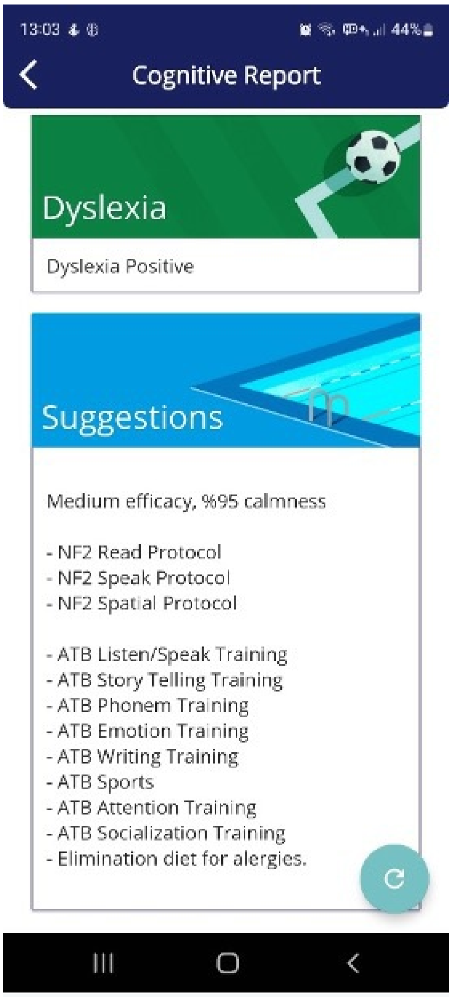

Figure 5. *The cognitive reports automatically generated after a 2-minute QEEG measurement*

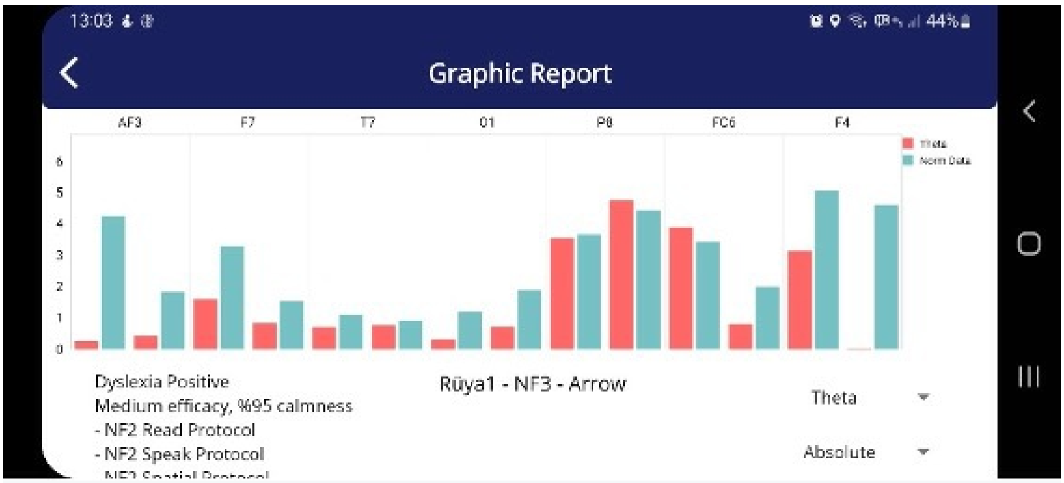

Figure 6. *The example cognitive reports that have been generated after a 2-minute QEEG measurement*

With the advancement of technologies, dyslexia detection starts at the age of 4 with 2-minute resting-state QEEG data with Auto Train Brain. It does not take much amount of time and money for the family to get this assessment. This measurement is standardized and an objective assessment, and not tiring for a child and it is definitely not as scary as visiting a psychiatrist. The child sits quietly for 2 minutes in a chair, the EEG headset is placed in 2 minutes, and the resting state EEG measurement was accomplished in 2 minutes, the results (whether he has dyslexia or not) are immediately ready and can be seen on the screen. If there would be a possibility of dyslexia, remedial actions could be taken as soon as possible. It is not necessary to wait until the child starts school or until the child is 8 years old. With the right intervention decided by a Child Neurologist, the symptoms of dyslexia can be reduced to a minimum until the child starts school at the age of 7. The families found the mobile app a feasible and acceptable solution for dyslexia detection at an earlier age. If children with dyslexia will continue their dyslexia training with Auto Train Brain at home, the diagnosis of dyslexia becomes very economic for the families. If it is a first-time measurement, they can get an assessment with Auto Train Brain in kindergarten which will cost less than buying the EEG equipment and the software subscription. In this way, the first-time assessments become very economic for the families too. The respondents in the survey were current users of Auto Train Brain, and they prefer to use technological solutions for improving the symptoms of dyslexia. The awareness of dyslexia and the possible training methods are not high in society. There are people who do not trust technological solutions and want to continue with traditional training methods for their dyslexic kids.

Although technology is ready to diagnose dyslexia with a high accuracy rate and improve the symptoms of dyslexia with mHealth solutions, families still think the economic impact of the whole solution is high to use at home. Either EEG headset prices should come down to make it possible to use at home, or the solution should be available in kindergartens. As the dyslexia market is a niche, EEG headset prices may not possibly be down in the short run.

After using the software for a longer period, families request other objective assessments to see the improvements after neurofeedback training. So, dyslexia biomarker detection becomes not enough for them, families require a training roadmap for their child to overcome this condition as fast as possible. Using ML methods to predict the next possible training will be our next challenge to add to the mobile app.

4.1. Limitations of the Study

The study's first issue is that it only has 207 participants and 12,420 repeated measurements from the same people. It would have been preferable if there had been more people in the trial.

The likelihood of placebo effects is the study's second restriction. Children who get one-on-one interactions and specialized therapies may enhance their functioning primarily due to the social and environmental influence of those interventions, according to Gaab et al. (2019). Because the control group was not given an alternative intervention, placebo effects might be a substantial source of improvement.

The study's third drawback is the maturation effects. Throughout their growth, all children's brains undergo major changes. As a result, QEEG modifications are anticipated to be influenced by maturation during the next six months.

5. Conclusions

The use of machine learning techniques in the dyslexia rehabilitation process may yield fresh insights. We developed a classification system for diagnosing dyslexia based on derived Z-scores from QEEG data and ANN in this work. The findings suggest that we will get fresh insight and a paradigm shift into the rehabilitation process.

Ethics approval and consent to participate

After the experimental procedure was explained to them by the research ethics committee, the study protocol was approved by the Yeditepe University Ethics Committee, and the clinical trial was registered with the Turkey Pharmaceuticals and Medical Devices Agency, all of the participants gave their informed consent (Nbr: 71146310-511.06,2.11.2018).

Availability of data and material

The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Code availability

None.

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