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A mobile app for dyslexia biomarker detection in children at home or at school: Feasibility, Acceptability, Economic impact, Pilot Study and Survey Results

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Abstract

The use of mobile apps in diagnosing health conditions has increased in recent years. We need a biomarker detection app for dyslexia because it potentially helps to prevent severe consequences through an early diagnosis that helps provide early intervention. No other research assessed the feasibility and acceptability of using this kind of mobile app to detect dyslexia at home or at school. Here we present a dyslexia biomarker detection app based on Z-scored QEEG data that can be used at home or school and has accomplished a high accuracy rate in diagnosing dyslexia. The mobile app can be used at home by parents or teachers at school. 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. Using the ANN machine learning method, children with dyslexia/ typically developing children (TDC) classification has been done with a high accuracy rate (98.8%). ANN yields the highest accuracy results with standardized QEEG data in the literature. A survey is created to assess the dyslexia biomarker detection app's feasibility, acceptability, and economic impact. The results have shown that the biomarker detection app is found feasible and acceptable by families, however, it is found expensive to use at home.

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1. Introduction

Dyslexia (as defined in DSM-5), or decoding difficulty, refers to children who have difficulty mastering the relationships between the spelling patterns of words and their pronunciations. These children typically read aloud inaccurately and slowly and experience additional problems with spelling (Snowling et al., 2012). Dyslexia is characterized by marked hypoactivation within the reading network, disrupted functional connectivity, and differences in structural connectivity in certain fiber tracts (Kuhl et al., 2020). It's characterized by problems with accurate and fluent word recognition and poor spelling skills (Snowling et al., 2012). 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).

Reading is an acquired ability for humans (Dehaene, 2005). The left hemispheric lateralization should be completed by the age of 7 before the child starts school and learns how to read (Koenig et al., 1990). During this period, as the child can not properly read and write, his self-esteem would go down and his academic life starts to be affected by the late intervention. With the help of computers and machine learning, the diagnosis of dyslexia can be done earlier, and remedial interventions may be taken much beforehand.

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. 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. 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 which use EEG scans, although it is a cheaper way to collect data, do not yield a high accuracy result to go to the market in the literature.

An artificial neural network (ANN) is a computational model that consists of several processing elements that receive inputs and deliver outputs based on their predefined activation functions. 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. The K-means algorithm identifies the k number of centroids, and then allocates every data point to the nearest cluster while keeping the centroids as small as possible. The 'means' in the K-means refers to averaging the data; that is, finding the centroid. Support Vector Machine(SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. 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 proficient readers and readers with dyslexia. 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).

This study aims to diagnose dyslexia using z-scored QEEG recordings from 14-channel band power data of both children with dyslexia and TDC with a high accuracy rate. Study tests the feasibility, acceptability, and economic impact of this app with a survey of families with dyslexia. This is the first research that investigated the use of dyslexia detection software in families who have children with dyslexia.

2. Methods and materials

2.1. Participants

96 children with pure dyslexia (M_{age}= 8.85, *SD* = 1.56; 76 males, 20 females; the ethnic group is white) who used a mobile app module at home 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). The children in the experimental group were diagnosed with dyslexia by doctors. Psychiatrists examine whether the individuals met the DSM-V dyslexia criteria. The children chosen to participate in the experiment were chosen at random. The participant's primary goal in the study is to use the software at home. Individuals were instructed to perform a 2-minute resting state EEG measurement for the purpose of data collection.

2.2. Materials

2.2.1. Electroencephalography

We have used EMOTIV's EPOC-X headsets in the experiments. The internal sampling rate of the headset was 2048 samples/s per channel. The EEG data is downsampled to 128 samples per second for each channel. Before the training, the EMOTIV EPOC-X headset was calibrated on children with dyslexia using EMOTIV APP mobile app. For all analyses in this work, theta (4–8 Hz), alpha (8–12 Hz), beta-1 (12–16 Hz), beta-2 (16–25 Hz), and gamma (25–45 Hz) bands of the 14-channel EEG data were recorded throughout the tests. Data from the delta (0–4 Hz) band was absent from the EMOTIV headset interfaces. It has been demonstrated that EMOTIV EPOC-X provides high-quality QEEG data (Badcock et al, 2013). In the dataset, there are 70 features (frequency band data; theta, alpha, beta1, beta2, gamma from 14 channels) that indicate whether a person has dyslexia or not. The information is gathered using electrodes on the Auto Brain Train device (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4). The labels for the characteristics reflect where the electrodes are placed.

2.2.2. Survey related to the usage of mobile app

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 at school? (5) Is the price of acquiring the solution (EEG headset and software subscription) high/ moderate/ low at home? (6) Is the price of 1-time measurement (children with dyslexia/ TDC classification) at school high/ moderate /low?
41 people participated in the survey. These are middle-aged parents (35- 45 years old, 60% female, 40% male). The socioeconomic status of the parents was middle class.

2.2.3. Socioeconomic status survey

To evaluate the socioeconomic status of the children, a survey of their parents was conducted. The poll includes inquiries about occupation, education (primary school, high school, and university), and income (basic income 6,000 TL, mid-level income 6,000 TL to 20,000 TL, high income >20,000 TL) (staff, blue-collar workers, white-collar workers). The study's inclusion criteria were that the participants were not on medication and did not have any other comorbid disorders than dyslexia and they came from middle-SES families. They lived in many cities around Turkey.

2.3. Procedures

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 using the EPOC-X and the app. The participant was requested to complete the QEEG measurement while relaxing and with their eyes open. This study has a limited sample size and is set up as a repeated measurement.

2-minute resting-state eyes-open theta, alpha, beta1, beta2, and gamma-band powers were measured (60 sessions per subject on average). This study uses a small sample size and multiple measures (12,420 sessions and 207 participants). The typically developing children's 2-minute resting-state eyes open QEEG data are gathered, and the data for the experimental and control groups are balanced to have an equal number of instances in each group.

2.6. 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) for all the data gathered from children with dyslexia and typically developing children. 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 doctor's diagnosis of the participant. The children with dyslexia and typically developing children's 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 best model is selected among many other varying hidden layers and activation functions. 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. The model is then converted to a TFLITE model and embedded into the mobile app.

The statistical analysis of the survey results was performed using SPSS.

3. Results

In this research, we have designed a Machine Learning algorithm to classify dyslexia and assessed the effectiveness with a survey of families with dyslexia. This study is a repeated assessment with a limited sample size (12,420 sessions) (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
1^{st} tanh , 2^{nd}softsign, 3^{rd} tanh , 4^{th}sigmoid,	**0.9880**	**0.988**	**0.05**	**0.98**
min max Scaler + 1^{st} *tanh* , 2^{nd}*softsign* 3^{rd} *tanh* , 4^{th}*sigmoid*	0.9863	0.986	0.07	0.96
1^{st} *tanh* , 2^{nd}*softsign* 3^{rd} *linear* , 4^{th}*sigmoid*	0.9818	0.982	0.09	0.95

In Table 1, the model architecture describes the activation functions at each level of ANN. 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 1, the model claims 72 TDC sessions for children with dyslexia sessions. On the other hand, the model states that 27 children with dyslexia sessions as TDC sessions out of 8301 samples. In this study, the number of false negatives is more important than the number of false positives. Although misclassifying TDC sessions as children with dyslexia -false positives- sessions would not create problems when it comes to the training, it is essential to consider children with dyslexia's sessions classified as TDC -a false negative- session predictions.

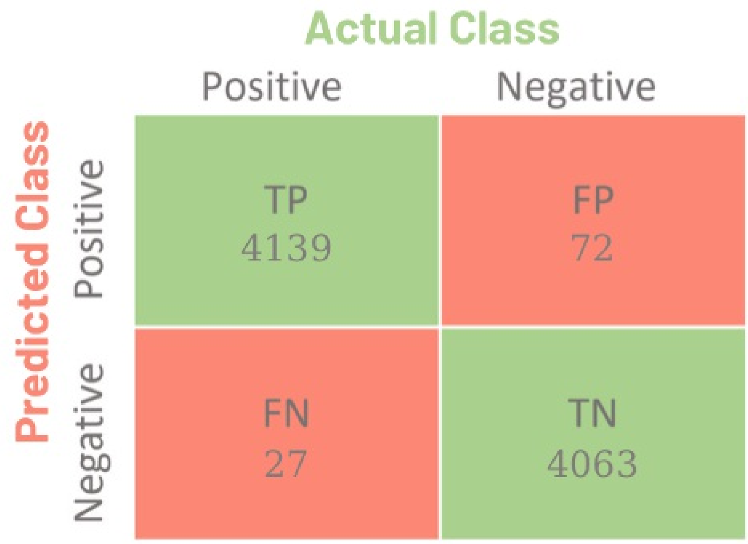

Figure 1. *Confusion matrix result of the best model*

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 2). 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.

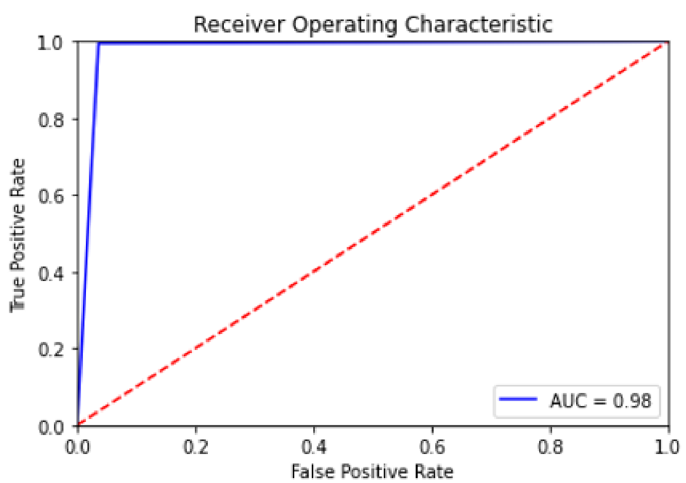

Figure 2. *Receiver Operating Characteristic Curve*

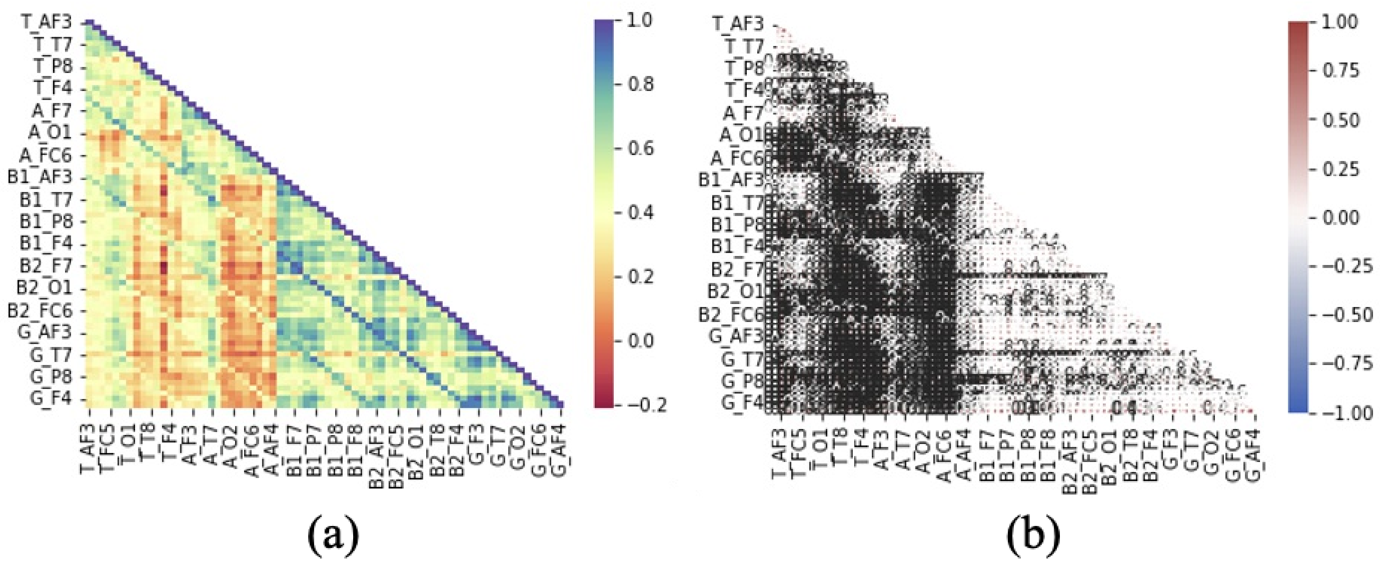

Figure 3. *Children with dyslexia data correlation matrix of features* $_{a(Heatmap),b(Filtered\ Heatmap)}$

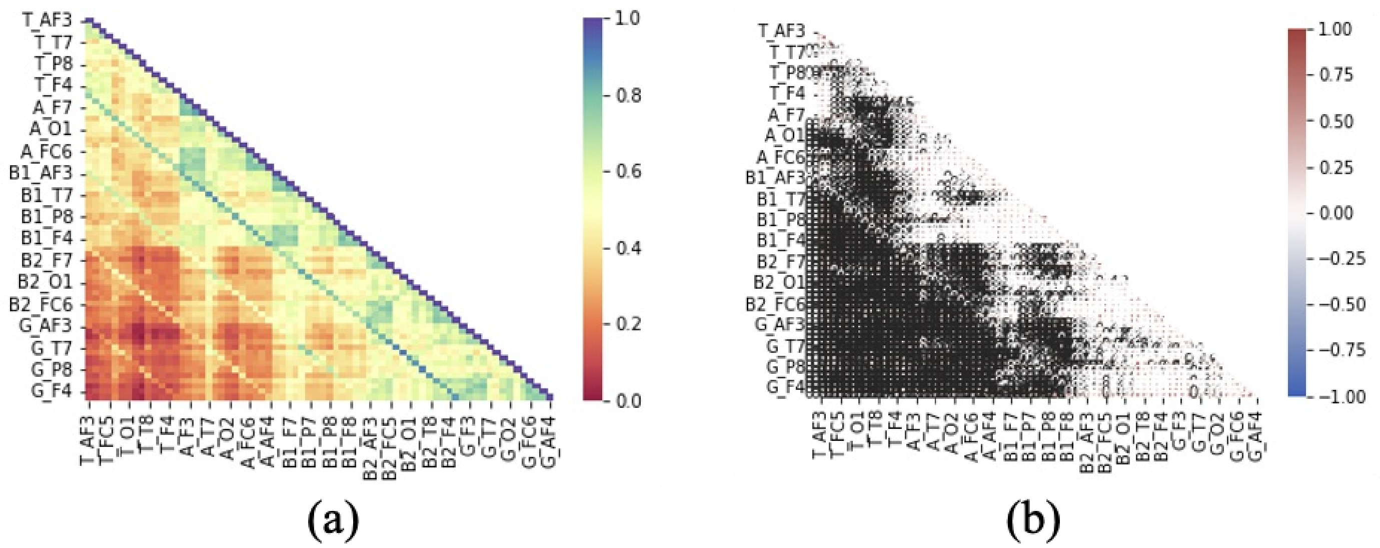

Figure 4. *TDC data correlation matrix of features* $_{a(Heatmap),b(Filtered\ Heatmap)}$

According to figure 3, children with dyslexia have higher correlations between the Alpha Band power at the right hemisphere with Beta-1, Beta-2, and Gamma values at the left and right hemispheres. Figure 4 indicates that theta band power at the left and the right hemisphere have higher correlations with the Beta-2 and Gamma values at the left and the right hemispheres. This findings indicate that the lefthemispheric dominance is not established for children with dyslexia yet.

The survey results (N= 41) indicate that 96% 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/TDC classification at home. 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. 22% of the respondents think the price of the one-time measurement (dyslexia/TDC classification) at school is expensive (Table 2, figure 5).

Table 2. Survey results on the usage of dyslexia diagnosis mobile app

Survey Questions	Results
Feasibility	96%
Acceptability	92%
Referral	83%
Prefer dyslexia detection usage at home	50%
Price high for usage at home	75%
Price high for one-time measurement at school	22%

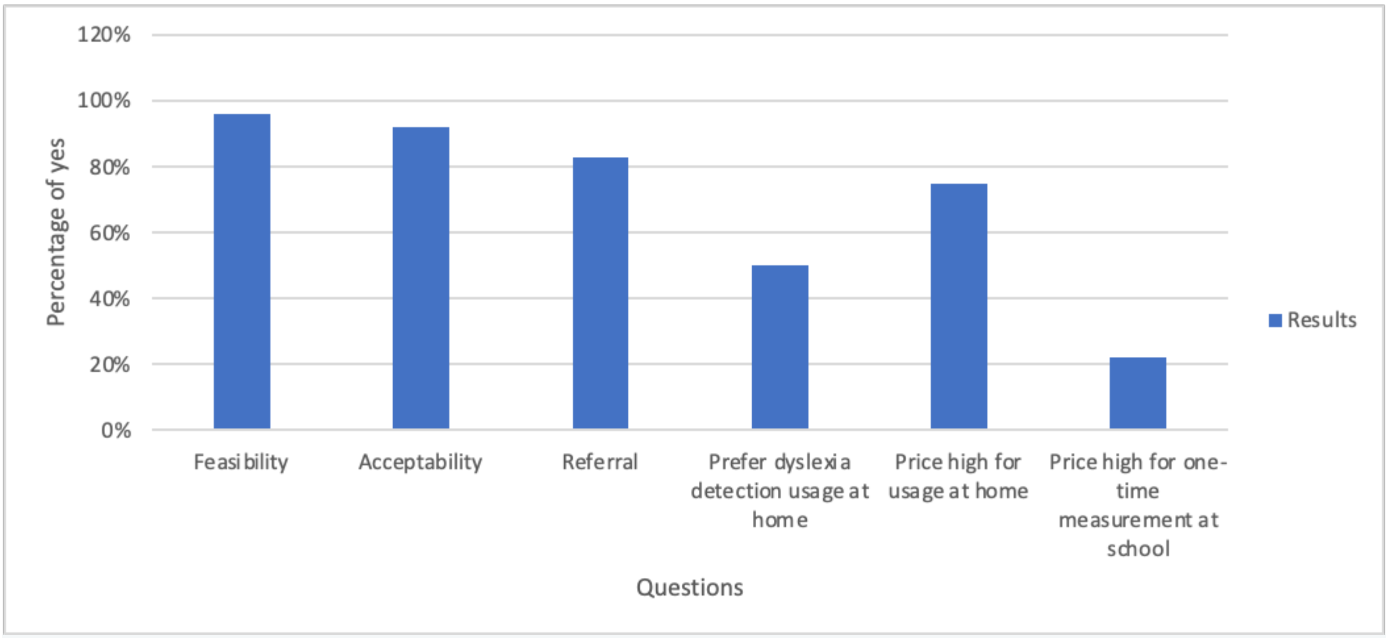

Figure 5. *Survey results as a bar chart*

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 a mobile app for everyday usage. Moreover, the feasibility, acceptability, and economic impact of the mobile app on families who have children with dyslexia are assessed with a survey in the real life afterward.

The QEEG scan correlation between children with dyslexia and TDC clearly shows that children with dyslexia data have a higher correlation between Theta, Beta, and Gamma signals than the TDC data.

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. 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 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 children with dyslexia and TDC (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. Even better results could be achieved by using different types of ANNS 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 on Android and iOS (Figure 6). In this way, the diagnosis of dyslexia with a high accuracy rate becomes possible with 2-minute resting-state QEEG data collected from a mobile app module (Figure 6, figure 7).

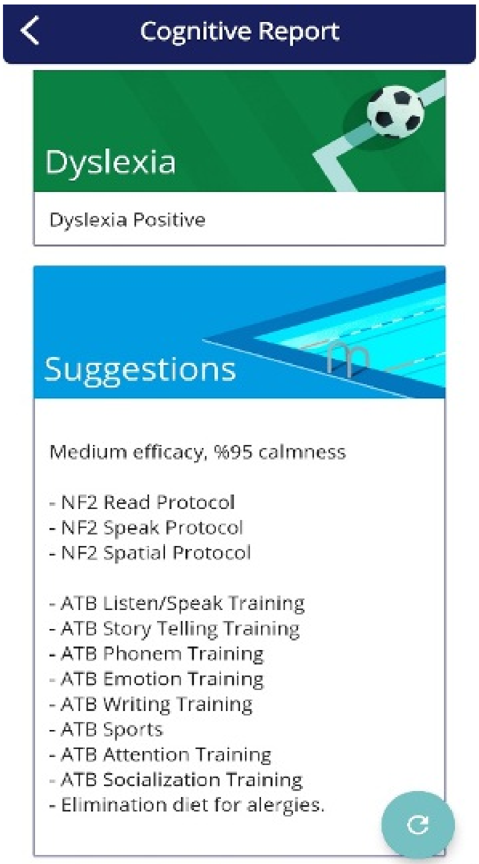

Figure 6. *The cognitive reports automatically generated after 2-minute QEEG Measurement*

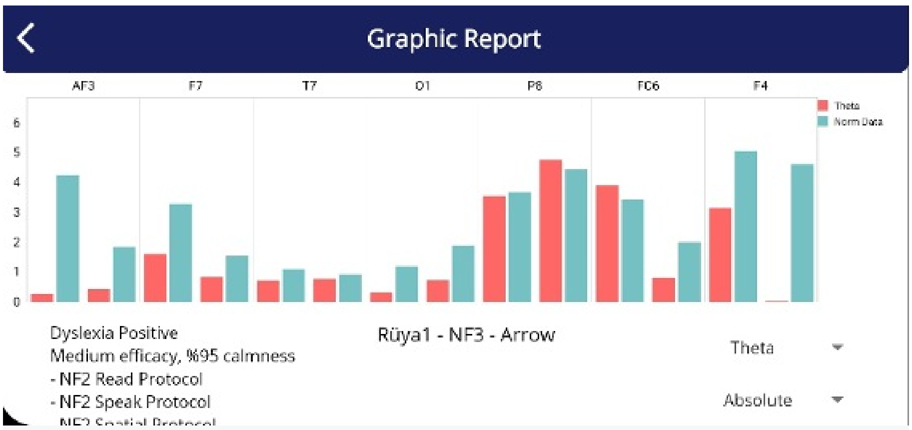

Figure 7. *The example cognitive reports that have been generated after a 2-minute QEEG Measurement*

With the advancement of technologies, dyslexia detection starts at the age of 4 with 2-minute resting-state QEEG data with a mobile app. 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. 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 can be taken as soon as possible. The families found the mobile app a feasible and acceptable solution for dyslexia detection. If children with dyslexia will continue their dyslexia training with a neurofeedback mobile app 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 an app at school 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 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 children with dyslexia.

Although technology is ready to diagnose dyslexia with a high accuracy rate and improve the symptoms of dyslexia with mobile health solutions, families still think the economic impact of the whole solution is high to use at home. Learning disabilities in generations impact the SES of families. The families who participated in our survey have middle SES, they still find the solution expensive although they have bought it. Either EEG headset prices should come down to make it possible for all families with dyslexia to use them at home, or the solution should also be available at school. As the dyslexia market is a niche (only 10% of society has dyslexia), EEG headset prices may not possibly be down in the short run.

Dyslexia biomarker detection becomes not enough for families, they require a training roadmap for their child to overcome this condition as fast as possible. Using ML methods to predict the next possible training or the level/scale of dyslexia will be our next challenge to add to the mobile app.

4.6. Limitations of the Study

The study's first drawback is that it only includes 207. The trial should have included more participants; that would have been optimal. 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

Dyslexia biomarker detection apps could provide new insights into the treatment of dyslexia. In this work, we created a classification scheme for dyslexia diagnosis based on generated Z-scores from QEEG data and ANN. Families will gain quicker, objective evaluation of their children with dyslexia by using the mobile app at home or at school as finding an expert in dyslexia may not be easy and reachable for families.

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 (TİTÇK), 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 on reasonable request.

Code availability

None.

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Declarations

Competing interests

None

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None

Authors' contributions

G.E. wrote the main manuscript text including the title, abstract, introduction, materials and methods, results, and discussion. G.E prepared tables and figures.

M.K. wrote the results and enhanced the materials and methods with the ANN method and algorithm. M.K. prepared tables and figures.

B.K. collected the data from normal children.

All authors reviewed the manuscript.

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