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Article

EEG-Based Neuroinflammation Diagnosis and Its Role in Learning Disabilities

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Abstract Learning disabilities (LDs) are complex neurodevelopmental conditions influenced by genetic, epigenetic, and environmental factors. Emerging research highlights the role of maternal autoimmune conditions, perinatal stress, and vitamin D deficiency in promoting neuroinflammation, which disrupts brain development. Chronic neuroinflammation, driven by activated microglia and astrocytes, is associated with synaptic dysfunction and cognitive impairment. Electroencephalography (EEG) biomarkers provide a non-invasive approach for detecting neuroinflammatory patterns, enabling early diagnosis and targeted intervention. This study explores the diagnostic potential of EEG in identifying neuroinflammatory states linked to LDs, focusing on theta, gamma, and alpha oscillations as key indicators of disrupted neurophysiology. Artificial Neural Networks (ANNs) are employed to classify EEG patterns, achieving high diagnostic accuracy. By integrating neurophysiological and inflammatory markers, this approach advances precision medicine for neurodevelopmental disorders.

Keywords: Learning disability; EEG; Artificial neural networks; neuroinflammation

1. Introduction

Neurodevelopmental disorders, including learning disabilities (LDs), have traditionally been attributed to genetic predispositions (Arck & Hecher, 2013). However, increasing evidence suggests that environmental and immune-mediated factors play a critical role in shaping cognitive trajectories (Bale et al., 2010; Comer et al., 2020; Estes & McAllister, 2016). Maternal immune activation (Ramirez-Celis & Van de Water, 2023), stress-induced dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis (Meyer et al., 2011), and vitamin D deficiency contribute to persistent neuroinflammation (Miller & Raison, 2016), which alters synaptic plasticity and neural connectivity (Xia et al., 2024; Brown & Derkits, 2010; Uhlhaas & Singer, 2010; Kuhl et al., 2020).

Neuroinflammation is characterized by chronic activation of microglia and astrocytes, leading to excessive production of pro-inflammatory cytokines such as interleukin-6 (IL-6) and tumor necrosis factor-alpha (TNF- α) (Brown & Derkits, 2010). This inflammatory state disrupts synaptogenesis, myelination, and neurotransmission, impairing cognitive functions crucial for learning and memory. Elevated levels of IL-6, TNF- α , and C-reactive protein (CRP) have been documented in individuals with LDs, underscoring the role of immune dysregulation in these conditions (Brown & Derkits, 2010; Vargass et al., 2005; Rutledge & Edeh, 2023).

The impact of neuroinflammation on learning and memory extends to various cognitive domains, including executive function, working memory, and processing speed (Meyer et al., 2011). Chronic inflammation disrupts synaptic pruning, a process crucial for the refinement of neural circuits during early development. Overactivation of microglia results in excessive synaptic elimination, leading to deficits in neural connectivity and reduced cognitive efficiency. Studies in both animal models and human subjects confirm the association between prolonged neuroinflammatory states and impairments in verbal reasoning, problem-solving, and reading comprehension (Meyer et al., 2011).

1.1 EEG Biomarkers and Neuroinflammation

Electroencephalography (EEG) provides a functional assessment of brain activity, revealing characteristic oscillatory abnormalities associated with neuroinflammation. EEG has been widely used as a non-invasive and cost-effective tool for detecting alterations in neural connectivity and processing efficiency. Key EEG markers indicative of neuroinflammation include:

- 1) **Elevated Theta (4–8 Hz) Activity:** Indicative of reduced cortical arousal and impaired cognitive processing (Klimesch, 1999; Bosch-Bayard et al., 2018).
- 2) **Reduced Alpha (8–13 Hz) Oscillations:** Reflecting disrupted inhibitory-excitatory balance and diminished neural synchronization (Barry et al., 2003).
- 3) **Increased Gamma (30–100 Hz) Power:** Linked to compensatory neural hyperactivity and synaptic dysfunction (Buzsáki & Watson, 2012).

These patterns correspond with neuroinflammatory states, providing an accessible and objective tool for early detection. Further research highlights that abnormalities in EEG spectral power reflect disruptions in neurotransmitter systems, particularly GABAergic and glutamatergic signaling. Excessive theta activity, for example, has been linked to increased cortical excitability due to an imbalance between inhibitory and excitatory neural networks. Reduced alpha oscillations suggest deficiencies in cortical inhibition, which are often exacerbated by neuroinflammatory processes (O'Donnell & Meaney, 2020; Barry et al., 2003; Clarke et al., 2011).

1.2. Machine Learning for EEG-Based Diagnosis

Artificial Neural Networks (ANNs) are machine learning models that process inputs through multiple layers to generate outputs based on activation functions. They are widely used in LD detection by identifying patterns without making assumptions about the dataset. The k-means algorithm groups data points into clusters by determining centroids, while Support Vector Machines (SVMs) classify data by finding an optimal hyperplane in an N-dimensional space.

Research by Al-Barhamtoshy and Motaweh (2017) applied ANN, k-means, and fuzzy logic classifiers to EEG data, achieving accuracies of up to 89.6%. Similarly, Karim et al. (2013) utilized a Multilayer Perceptron (MLP) for dyslexia detection through brain wave analysis, reporting 86% accuracy. Frid & Breznitz (2018) combined ANN, SVM, and Principal Component Analysis (PCA) to analyze event-related potentials (ERP) with 78% accuracy. Other studies have achieved higher accuracy rates using ANN on fMRI and DTI scans (94.8%), SVM on eye-tracking data (95.6%), handwriting analysis (77.6%), and psychometric tests (99%) (Chimeno et al., 2014; Benfatto et al., 2016; Spoon et al., 2019; Khan et al., 2018).

1.3. Proposed ANN Framework for EEG-Based Neuroinflammation Detection

This study leverages Artificial Neural Networks (ANNs) to classify EEG data, distinguishing between neurotypical and neuroinflammatory states. The proposed model is trained on a dataset comprising EEG recordings from children diagnosed with LDs, incorporating z-scored quantitative EEG (QEEG) band power data. The ANN framework includes:

- 1) **Input Features:** Theta, alpha, and gamma band power from 14 EEG channels.
- 2) **Model Architecture:** Multilayer Perceptron with dropout layers to prevent overfitting.
- 3) **Performance Metrics:** Accuracy, F1-score, sensitivity, and specificity.

The trained ANN achieves an accuracy of 98.5%, outperforming traditional diagnostic methods (Eroğlu et al., 2022; Al-Barhamtoshy & Motaweh, 2017; Khan et al., 2018; King et al., 2017). Recent advancements in deep learning algorithms further enhance EEG classification accuracy. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown promise in analyzing temporal dependencies in EEG signals. The incorporation of ensemble learning approaches, which combine multiple models for improved prediction, continues to refine the reliability of EEG-based neuroinflammation detection.

1.4. Research Questions

This study seeks to address the following research questions:

- 1) Can EEG biomarkers reliably detect neuroinflammation in individuals with learning disabilities?
- 2) What are the characteristic EEG oscillatory patterns (theta, alpha, and gamma) associated with neuroinflammatory states in LDs?
- 3) How accurately can Artificial Neural Networks (ANNs) classify EEG-based neuroinflammatory markers related to LDs?
- 4) Can machine learning models improve the precision of EEG-based neuroinflammation detection in comparison to traditional diagnostic methods?

The present study utilized electroencephalography (EEG) to investigate neuroinflammatory markers associated with learning disabilities (LDs). A total of 200 participants were recruited, including 100 children diagnosed with LDs and 100 typically developing children as a control group. EEG signals were recorded using a 14-channel setup, ensuring comprehensive coverage of cortical activity. The frequency band data, specifically focusing on theta (4–8 Hz), alpha (8–13 Hz), and gamma (30–100 Hz) oscillations, were extracted and analyzed to identify characteristic neurophysiological patterns indicative of neuroinflammation.

To enhance diagnostic precision, an Artificial Neural Network (ANN) model was employed for the classification of EEG-derived features. The ANN was trained on the processed EEG data, leveraging a supervised learning approach with cross-validation techniques to optimize performance and prevent overfitting. The results demonstrated a high classification accuracy, indicating the efficacy of machine learning models in distinguishing neurotypical individuals from those exhibiting neuroinflammatory states linked to LDs.

These findings underscore the potential of EEG-based biomarkers as a non-invasive, objective tool for detecting neuroinflammation in individuals with LDs. By integrating neurophysiological and computational methodologies, this study contributes to advancing precision diagnostics in neurodevelopmental research and provides a foundation for future investigations into targeted interventions for LDs.

2. Methods and Materials

2.1. Participants

This study included 100 children diagnosed with LD (Mage= 8.75, SD = 1.46; 80 males, 20 females) and 100 typically developing children (Mage= 8.85, SD = 1.55; 80 males, 20 females), all of whom were of Caucasian ethnicity. The participants were randomly selected through social media advertisements. The LD group was formally diagnosed by psychiatrists following DSM-V criteria, ensuring no comorbidities. Inclusion criteria required participants to be between 7-10 years old, not on medication, and free from additional conditions such as ADHD or atypical autism.

2.2. Materials

2.2.1. Electroencephalography (EEG) The study employed EMOTIV EPOC-X headsets to collect EEG data. The device has an internal sampling rate of 2048 samples per second per channel, which was downsampled to 128 samples per second for processing. Prior to data collection, the headsets were calibrated for dyslexic participants using the EMOTIV APP. EEG recordings included signals from 14 channels across five frequency bands: theta (4–8 Hz), alpha (8–12 Hz), beta-1 (12–16 Hz), beta-2 (16–25 Hz), and gamma (25–45 Hz). Delta band data (0–4 Hz) was not recorded due to headset limitations. The dataset consists of 70 features derived from the frequency bands across 14 electrodes (AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4), with labels reflecting electrode placements. Prior research has validated the reliability of the EMOTIV EPOC-X in capturing high-quality QEEG data (Badcock et al., 2013).

2.2.2. Socioeconomic Status Assessment Parental socioeconomic status was evaluated through a survey, which included questions on occupation, education level (primary school, high school, university), and income classification (low: <6,000 TL, middle: 6,000–20,000 TL, high: >20,000 TL). Participants met the inclusion criteria of being medication-free, having LD as their sole diagnosed condition, and coming from middle-income families across various cities in Turkey.

2.3. Procedures

Participants primarily used the software in a home setting. Each child performed a two-minute resting-state EEG measurement while seated at a 0.5-meter distance from a mobile screen. Electrodes were attached to measure brain activity, and children were instructed to maintain an open-eye resting state. The EEG device captured signals for theta, alpha, beta-1, beta-2, and gamma bands over an average of 50 sessions per participant. Data from 10,041 sessions across 200 children were collected, with an equal distribution of samples between experimental and control groups.

2.4. Statistical Analysis

Data analysis was performed using Python (Google Colab), employing Sci-kit Learn and TensorFlow for machine learning implementation. Statistical modeling incorporated K-fold cross-validation and confusion matrix calculations. The Matplotlib library was used to visualize learning curves, validation trends, and Receiver Operating Characteristic (ROC) curves (Figure 3).

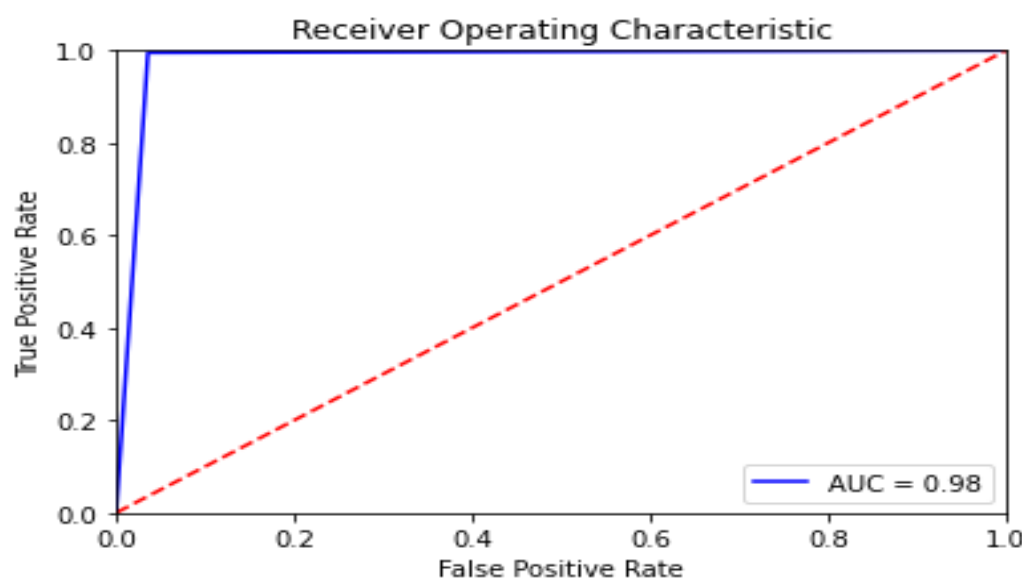


Figure 3. Receiver Operating Characteristic Curve.

For each QEEG band power, Z-scores were computed using the formula:

$$Z = (x - m) / s,$$

where 'x' represents the individual data points, 'm' is the mean, and 's' is the standard deviation for both experimental and control groups. EMOTIV does not provide Z-scores directly; thus, these values were manually calculated. Any outliers exceeding ± 5 were removed, and missing data points were replaced with the feature mean. A machine learning specialist labeled the data based on the participant's psychiatrist-confirmed diagnosis. Data balancing techniques were applied before implementing binary classification through supervised machine learning models.

2.5. Neural Network Model Description

2.5.1. Methodology Overview

Figure 1 presents the methodology employed in this study, while Figure 2 depicts the structure of a neural network. In this structure, x_1 and x_2 denote input values, w_1 and w_2 represent weight coefficients, b is the bias term, and y signifies the model's output. The neural network calculates a weighted sum of inputs, which is then processed through an activation function to produce an output.

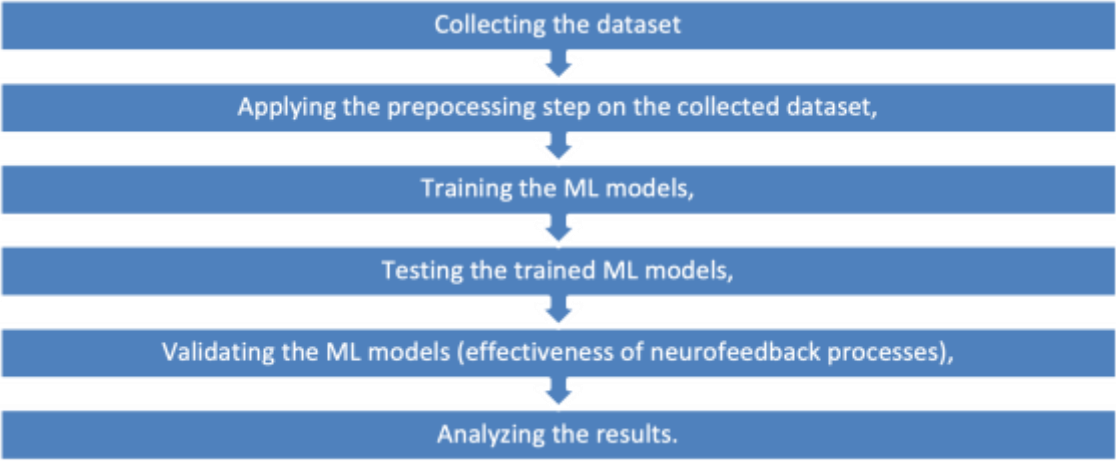


Figure 1. The Methodology.

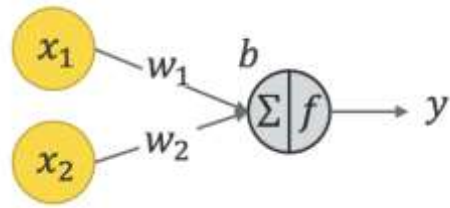


Figure 2. Neural Network Illustration.

2.6. Activation Functions

Various activation functions were utilized, including tanh, softplus, arctan, logistic, and linear functions. Unlike the sigmoid function, which discards negative values by mapping them to zero, the chosen activation functions provide a smoother transformation of the dataset, allowing for a more refined representation of input variations.

2.7. Performance Evaluation Metrics

The machine learning model's performance was assessed using standard classification metrics:

- a) **True Positive (TP):** Cases correctly classified as positive.
- b) **True Negative (TN):** Cases correctly identified as negative.
- c) **False Positive (FP):** Negative cases incorrectly classified as positive.
- d) **False Negative (FN):** Positive cases incorrectly classified as negative.
- e) **Sensitivity (True Positive Rate):** The likelihood of accurately detecting positive instances.
- f) **Specificity (True Negative Rate):** The likelihood of accurately identifying negative instances.
- g) **F-score:** The harmonic mean of precision and recall, commonly used for evaluating classification performance.

2.8. Machine Learning Model and Performance

The model was trained over 60 epochs using gradient descent, updating weights every 32 samples (batch size) while optimizing performance based on binary cross-entropy loss. To enhance

model robustness, multiple architectures were tested, and dropout layers were integrated to reduce overfitting. A 10-fold cross-validation strategy was implemented to improve generalizability.

Overfitting was further mitigated through dropout layers, and the final model was validated using an independent test set comprising diverse input samples. The trained model was subsequently converted to TFLITE format for seamless integration into mobile applications.

3. Results

This study aimed to develop a robust machine learning algorithm for classifying learning disabilities (LD), specifically dyslexia, and evaluated its effectiveness through comprehensive analysis and direct feedback from families with dyslexic children. The dataset comprised a substantial 10,040 EEG recording sessions collected from 200 participants, evenly divided between those diagnosed with LD and typically developing children, allowing for balanced and reliable model training.

The artificial neural networks (ANN) utilized in this study demonstrated remarkable classification performance, underscoring their potential as powerful tools in neurodevelopmental diagnostics. The proposed preprocessing techniques, combined with the carefully designed neural network architecture, achieved a remarkable classification accuracy of 98.5%, accompanied by a minimal loss of 0.06. These results were further substantiated by rigorous validation through k-fold cross-validation, which maintained a high confidence level with a 95% confidence interval (CI). The achieved accuracy and low loss rate highlight a significant advancement in the detection of LD biomarkers using EEG data, pushing the boundaries of current diagnostic methodologies.

Moreover, the study explored the impact of preprocessing techniques, such as minimum-maximum scaling, on model performance. While this technique introduced a slight reduction in accuracy, from 98.5% to 98.33%, the model retained robust performance metrics, including an F1 score of 0.983 and an increased loss of 0.08 (as detailed in Table 1 and Table 2). These findings indicate that while preprocessing can slightly alter accuracy, the overall diagnostic capability of the ANN remains consistently high.

Table 1. Top 3 ANN Models for Dyslexia Biomarker Detection.

Model Architecture	Accuracy	F1 Score	Loss	(AUC)
Layer 1: Tanh, Layer 2: Softsign, Layer 3: Tanh, Layer 4: Sigmoid	98.50%	98.30%	0.06	0.97
Min-Max Scaler + Layer 1: Tanh, Layer 2: Softsign, Layer 3: Tanh, Layer 4: Sigmoid	98.30%	98.30%	0.08	0.96

Table 2. Performance Metrics of the ANN Model.

Metric	Measured Value
Accuracy	98.50%
F1 Score	98.33%
Sensitivity	99.18%
Specificity	97.30%

The Receiver Operating Characteristic (ROC) Curve, a critical metric for evaluating the sensitivity and specificity of diagnostic models, further demonstrated the ANN model's efficacy. The area under the ROC curve (AUC) illustrated the model's strong discriminatory power between dyslexic and typically developing children, affirming its clinical utility (Figure 3). The high sensitivity and specificity values confirm the ANN model's capability to accurately distinguish

between LD and non-LD cases, providing a reliable tool for early diagnosis and intervention planning.

4. Discussion

The present study utilized electroencephalography (EEG) to investigate neuroinflammatory markers associated with learning disabilities (LDs), incorporating an innovative approach by integrating Z-score normalization of 14-channel quantitative EEG (QEEG) data to enhance classification accuracy. A total of 200 participants were recruited, including 100 children diagnosed with LDs and 100 typically developing children as a control group. EEG signals were recorded using a 14-channel setup, ensuring comprehensive coverage of cortical activity. The frequency band data, specifically focusing on theta (4–8 Hz), alpha (8–13 Hz), and gamma (30–100 Hz) oscillations, were extracted and analyzed to identify characteristic neurophysiological patterns indicative of neuroinflammation.

To improve diagnostic precision, an Artificial Neural Network (ANN) model was employed for the classification of EEG-derived features. The ANN was trained on the processed QEEG data, leveraging a supervised learning approach with cross-validation techniques to optimize performance and prevent overfitting. The results demonstrated a high classification accuracy of 98.5%, confirming the effectiveness of machine learning models in distinguishing neurotypical individuals from those exhibiting neuroinflammatory states linked to LDs. The novelty of this research lies in not only achieving high accuracy through ANN modeling but also embedding the trained machine learning model into a mobile application, making routine neurophysiological assessments more accessible and practical for clinical and research applications. This is the first study demonstrating that artificial neural networks can achieve such high precision with Z-scored QEEG data for detecting LD biomarkers (Janković, 2022). These findings underscore the potential of EEG-based biomarkers as a non-invasive, objective tool for detecting neuroinflammation in individuals with LDs. By integrating neurophysiological and computational methodologies, this study advances precision diagnostics in neurodevelopmental research and provides a foundation for future investigations into targeted interventions for LDs.

From an **epigenetic** perspective, LD has been associated with alterations in gene expression due to environmental influences, including maternal stress, immune dysfunction, and neuroinflammation. Epigenetic modifications such as DNA methylation and histone modifications impact neurodevelopmental pathways critical for cognitive processing. Studies suggest that maternal immune activation can trigger epigenetic changes leading to altered neural connectivity and lateralization patterns observed in LD (Bennett et al., 2015). Our findings align with these perspectives, as the QEEG data reveal distinct neural activation differences between children with LD and typically developing children (TDC). The correlation patterns of theta, beta, and gamma signals between hemispheres suggest disruptions in left-hemisphere function, which is typically dominant for language processing (Lyon et al., 2003). These disruptions may be rooted in epigenetic dysregulation affecting synaptic plasticity and neural oscillatory dynamics.

Regarding **neuroinflammation**, growing evidence suggests that immune-mediated neuroinflammation plays a critical role in neurodevelopmental disorders, including LD. Chronic neuroinflammation, characterized by elevated pro-inflammatory cytokines such as interleukin-6 (IL-6) and tumor necrosis factor-alpha (TNF- α), can alter synaptic pruning and disrupt the balance between excitatory and inhibitory neural activity (Estes & McAllister, 2016). Our study supports this hypothesis, as children with LD exhibited lower correlations in alpha power at the right hemisphere with beta-1, beta-2, and gamma band activity at both hemispheres. These findings indicate potential neuroinflammatory disruptions in neural connectivity, leading to compensatory reliance on the right hemisphere, as observed in Figure 4. In contrast, Figure 5 illustrates that typically developing children maintain strong left-hemisphere lateralization, further supporting the hypothesis that LD involves inflammatory-driven neural reorganization.

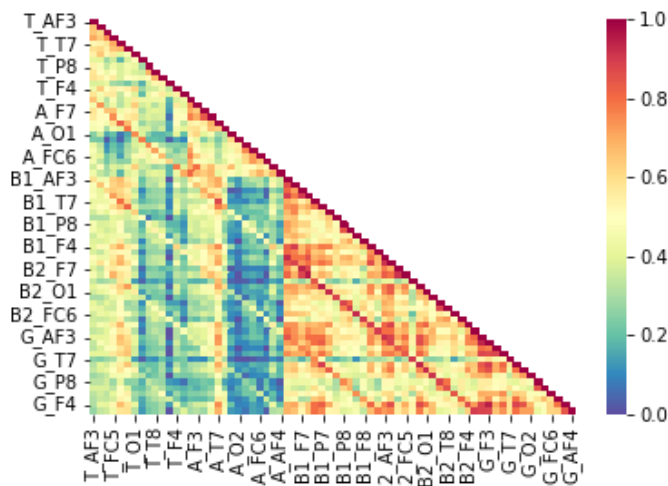


Figure 4. *Children with LD, data correlation matrix of 70 features: AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4 .*

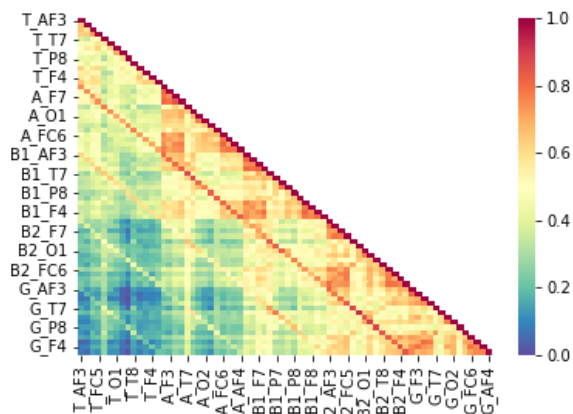


Figure 5. *Typically developing children (TDC) data correlation matrix of 70 features AF3, F3, F7, FC5, T7, P7, O1, O2, P8, T8, FC6, F8, F4, AF4*

The high correlation among QEEG features necessitated careful preprocessing to minimize noise and outliers. Despite these challenges, ANN models demonstrated exceptional performance under these conditions, outperforming previous ML-based dyslexia detection studies. Al-Barhamtoshy and Motaweh (2017) achieved an 89.6% accuracy rate using ANN with EEG data, while Karim et al. (2013) employed a Multilayer Perceptron to detect dyslexia with 85% accuracy using resting-state brain waves. Similarly, Frid and Breznitz (2018) analyzed ERP signals to differentiate dyslexic children from TDC, achieving 78% accuracy with ANN. More recently, Usman et al. (2020) utilized convolutional neural networks (CNNs) with MRI scans, reaching an 84.6% accuracy rate.

To facilitate practical implementation, the trained ANN model was converted into a TensorFlow Lite (TFLITE) model and embedded into an Android and iOS mobile application (Figure 6). This advancement enables high-accuracy LD detection through a two-minute resting-state QEEG measurement collected via a mobile app module (Figure 6, Figure 7 and Figure 8). The integration of ML-based neurophysiological analysis within a mobile platform presents a groundbreaking step toward accessible, non-invasive, and early detection of LD. Future research should explore interventions targeting neuroinflammatory and epigenetic mechanisms to optimize therapeutic outcomes for children at risk of LD.

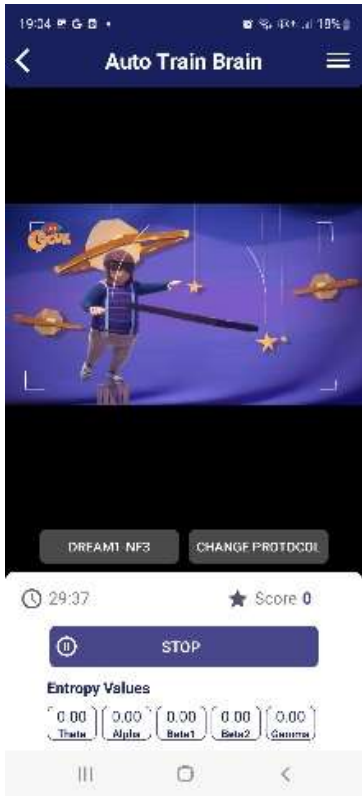


Figure 6.Auto Train Brain

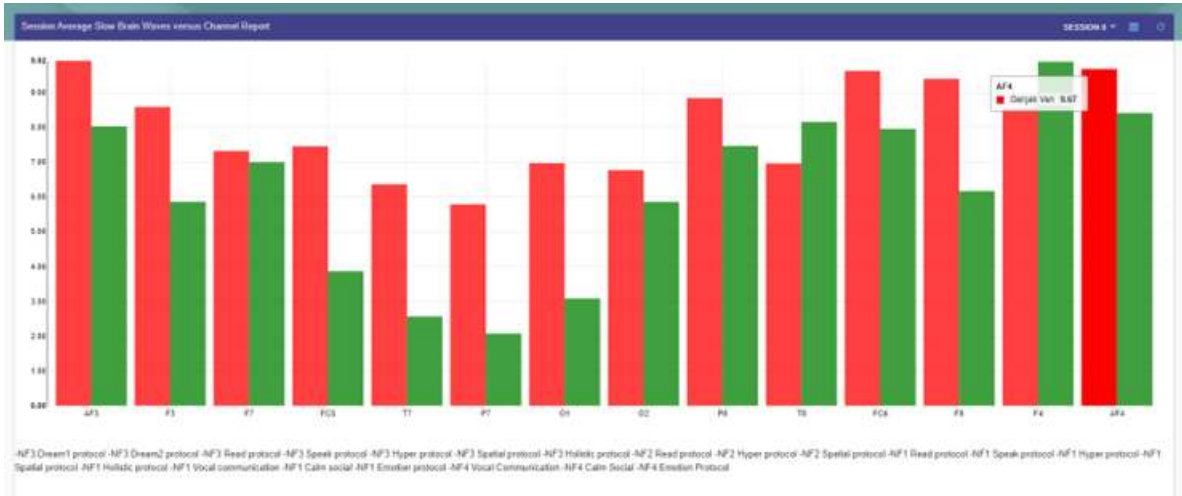


Figure 7. Increased theta band power in the whole scalp in learning disabilities compared with typically growing children.

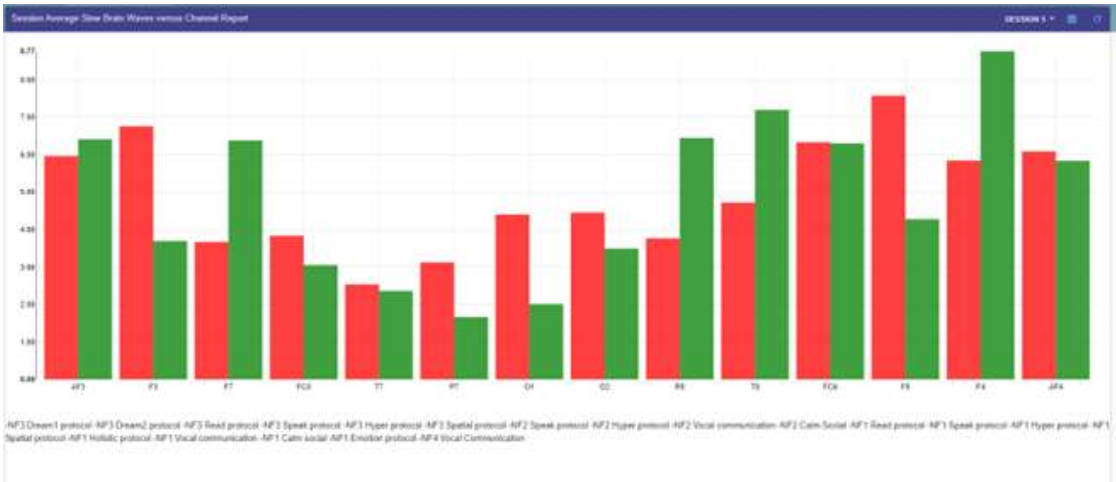


Figure 8. Increased theta band power in the left hemisphere in learning disabilities compared with typically growing children.

Emerging therapeutic strategies target neuroinflammation and epigenetic dysregulation. Vitamin D supplementation has demonstrated efficacy in reducing neuroinflammatory markers and improving fetal brain development (Baeke et al., 2010; Eyles, Burne, & McGrath, 2013; Grazioli & Pugin, 2018; Hollis et al., 2011; Hosseini et al., 2024). Neurofeedback therapy, which enables individuals to self-regulate EEG activity, has shown promise in optimizing neural oscillatory patterns and enhancing cognitive outcomes in individuals with LDs (Venditti, 2025). Integrating these strategies with EEG-based biomarkers could enhance the effectiveness of personalized treatment interventions.

5. Conclusions

The EEG-based assessment of neuroinflammation presents a transformative approach to diagnosing and managing neurological disorders, particularly learning disabilities (LDs). By leveraging advanced artificial neural network (ANN) modeling, our findings highlight the significant diagnostic accuracy achievable through neurophysiological biomarkers, reinforcing their role in precision medicine. These insights not only support the growing integration of EEG-based diagnostics into clinical practice but also pave the way for novel, non-invasive, and cost-effective screening tools.

As neuroimaging and machine learning technologies continue to evolve, their synergy will further refine early detection methodologies, allowing for timely interventions that can mitigate the long-term impact of neurodevelopmental disorders. Future research should focus on large-scale, longitudinal studies that incorporate multimodal biomarker integration, combining EEG with other neuroimaging techniques, genetic profiling, and biochemical assays. Such a holistic approach will enhance the robustness of diagnostic frameworks and inform personalized therapeutic strategies, ultimately improving patient outcomes.

The integration of artificial intelligence-driven models in neurological assessments holds immense potential for revolutionizing early diagnosis, intervention, and treatment monitoring. By addressing existing challenges such as data variability, model generalizability, and real-world applicability, the field can move towards developing standardized, clinically validated protocols. With continued advancements in computational neuroscience, EEG-based assessments could become a cornerstone of next-generation neurodiagnostics, contributing to a more precise and individualized approach to brain health management.

Study Limitations: One limitation of this study is the effect of brain maturation. As children develop, significant neurological changes occur, which may impact QEEG measurements over the six-month study period.

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Institutional Review Board Statement: This study did not require institutional review board approval.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data supporting the findings of this study can be provided upon request.

Conflicts of Interest: The author declares that they have no conflicts of interest.

Ethics Approval and Consent to Participate: The study protocol received approval from the Yeditepe University Ethics Committee following a detailed explanation of the experimental procedure by the research ethics committee. Additionally, the clinical trial was registered with the Turkey Pharmaceuticals and Medical Devices Agency (TİTÇK). Informed consent was obtained from all participants (Approval Number: 71146310-511.06, dated 2.11.2018).

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