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Classification of EEG signals from young adults with dyslexia combining a Brain Computer Interface device and an Interactive Linguistic Software Tool

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ABSTRACT

The magnocellular pathway deficit theory has long been considered to be a possible cause for dyslexia, providing an alternative method to explain auditory and visual processing deficits. Several studies have attempted to classify these deficits with the application of machine learning in anatomical brain imaging, rendering the classification techniques using EEG graph measures both robust and reliable. In this paper, a classification of university students with and without dyslexia is attempted with the use of a Brain Computer Interface (BCI) Device and an Interactive Linguistic Software Tool in order to validate the application of such a device in classifying dyslexia in a higher education population. EEG signals acquired from a wearable, sensory EEG recording device from 12 university students with dyslexia along with 14 typically developed, age matched individuals are recorded, while participants were examined in three different experimental conditions: a) auditory discrimination, b) visual recognition c) visual recognition with background music. Spectral features extracted from each EEG rhythm (δ, θ, α, β, γ) are used to train a Random Forests classifier, aiming to identify quantitative EEG features that characterize dyslexia in different brain regions. Results show high levels of accuracy, sensitivity and specificity (above 95%) in the entire brain, followed by the left and right hemisphere, with the highest discrimination performance reported during the third experimental condition with the presence of background music. Different experimental conditions provide high classification accuracy that results in correct discrimination between higher education students with and without dyslexia.

1. Introduction

Dyslexia is one of the most frequent specific developmental learning disorders and is estimated to affect 5–15% of the student population [1,2] although estimates vary widely depending on cut-off criteria on reading assessment scales, and a great diversity of theoretical outlooks on dyslexia [3]. Dyslexia is described as a particular deficit in reading acquisition that cannot be reported for by low IQ, poor educational opportunities, or an obvious sensory or neurological damage [3]. It has often been related to severe deficits in reading and spelling skills which are not attributed to intellectual disabilities, inadequate schooling and socio-cultural conditions, and neurological, visual, or auditory impairment [4,5]. It often co-occurs with phonological deficits [6] that persist in adult life [7,8], and include one or several aspects of phonological processing, like mentally manipulating speech sounds (phonological awareness), storing phonological material for a few seconds (verbal short-term memory), and rapidly retrieving long-term phonological representations [9].

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Within the past decades, a variety of theories have emerged to explain the origins of dyslexia, including the phonological and the cerebral deficit hypotheses. According to the first which has been deemed as the most influential theory, reading and writing difficulties are caused by language disabilities within the phonological sector [10-14] where people with dyslexia are unable to efficiently decode written letters (graphemes) into their corresponding sounds (phonemes). Conversely, the cerebral deficit hypothesis [15,16] suggests that impairments are caused by impaired articulatory skill acquisition, which in turn results from an ontogenetic cerebellar dysfunction. From a behavioral perspective, the difficulties of people with dyslexia in time estimation, motor skill and working memory, and in balance tasks might be explained by the cerebral deficit hypothesis [17]. In addition, a number of recent studies have found that other factors such as underlying primary auditory processing deficit [18,19], impaired visual processing [20,21], attentional deficits [22,23], impaired eye movements [24], and abnormalities of processing [25] have been widely correlated to dyslexia as the main or contributing causal factors.

Moreover, Livingstone and Galaburda [26] after their research concluded that the magnocellulars of the Central Nervous System of people with dyslexia were smaller in size and disorganised compared to their typical counterparts, indicating that a general sensory magnocellular abnormality might lead to difficulties in processing sensory information, thus resulting in disruption of normal language learning and processing [27]. The magnocellular theory is a theory that unifies both the hypothesis of cerebellar deficit and the hypotheses of visual or auditory deficits. Magnocellular processing deficits have long been reported [28,29] to be a possible cause for dyslexia and providing an alternative method to explain sequencing and visual processing deficits. Overall, this hypothesis refers to the abnormalities in magnocellular sensory pathways which impair the processing of fast incoming visual or auditory stimuli [30,31], as they carry information about motion, overall shape, and small light–dark changes. Although this theoretical approach has not been without its critics [32,33], it has attracted major support from a large body of research [27,34,35]. Evidently, it can be inferred that when a number of deficits combine together it may result in reading difficulties, thus, supporting the view that dyslexia is a multifactorial disorder [36]. Consequently, the search for a "unique dyslexia deficit" is likely inadequate when it comes to explaining this complex neurodevelopmental disorder [37-39].

Another line of research has focused on elucidating the neurobiological differences between the hemispheres and assessing commonalities between the various subtypes of children and adults with dyslexia [40]. Specifically, it has been suggested that the development of interhemispheric functional asymmetry may be deregulated in people with dyslexia [41]. Consequently, the transfer of motor and sensory information between the two hemispheres is degraded due to changes in the corpus callosum of dyslexic brain. These research efforts show that subtle developmental changes or asymmetries in the network of many brain structures may be at the bases of sensory and cognitive problems in dyslexia [42,43].

Although the vast majority of studies regarding dyslexia has been carried out in children population and stressed its continuity into adolescence and adulthood [44,45], a large literature gap (research in adult subjects represents almost 6% of all research in dyslexia) concerning the persistence of reading difficulties during these periods, does still exist [46]. Even fewer are the studies where neuroimaging techniques, and more specifically EEG signals, have been connected to adult research suggesting that neurocognitive deficits, including connectivity abnormalities, persist in dyslexia during adulthood [47]. In a study of 28 adults with dyslexia and 36 typically reading adults, Gonzalez et al. [48] assessed functional connectivity strength with the phase lag index (PLI) in order to investigate the EEG functional networks at rest for each frequency band (δ, θ, α, β) reporting significant group differences in the α band (8–13 Hz).

Mahe et al. [49,50] have conducted experiments using evoked potentials resulting in impaired N170 print tuning in adults with dyslexia during word recognition, longer latencies, more errors for pseudowords, and a lack of hemispheric specialization. Similarly, Shany and Breznitz [51] reported lower N170 activation in the visual association cortex in Hebrew speakers with dyslexia. In addition, there has been a number of studies which resulted in decreased P3b amplitudes whether this involved atypical perception [52] or reading pseudohomophones [53]. However, Fosker and Thierry [54] implementing a phonological discrimination task found a deficit in N1 modulation without reporting any significant differences in P2, N2, P3a, and P3b in individuals with dyslexia. In the same line of research, there have been findings concerning decreased amplitude and latency in mismatch negativity in the left hemisphere during phoneme [55], syllable [56], and tone discrimination [57].

2. Related work

Many neuroimaging techniques have been proposed in order to enable researchers to comprehend how decoding and sight recognition function both in people with or without dyslexia [58]. These distinctive brain behaviors have been portrayed through functional Magnetic Resonance Imaging (fMRI) [59,60], Magnetoencephalography (MEG) [61], Diffusion Tensor Imaging (DTI) [62,63], Voxel-Based Morphometry (VBM) [64,65] and Positron Emission Tomography (PET) [66] to name but a few techniques and studies.

As most of the previous techniques may limit the research on people with dyslexia due to radioactive application and body movement limitation [67], Electroencephalography (EEG) technique, which is considered to be a non-invasive measure of brain function, has been widely used to assess brain behaviors offering additional insights into cortical lateralization models [68,69]. The most studied component of ERPs is the P300 waveform [70], as it reflects higher-order cognitive processes such as stimulus evaluation and categorization [71].

A study carried out by Arns et al. [72] using EEG signals in a resting state, revealed unique brain activation patterns in children with dyslexia showing increased slow θ and δ activity in the frontal and right temporal areas of the brain and an increased β activity at F7. Similarly, Goswami [19] proposed that a specific difficulty with atypical cortical oscillations in the θ (4–7 Hz) or in the δ (1–4 Hz) frequency band may lead to impaired auditory rhythmic entrainment, thereby leading to processing deficits at the syllable level, whereas Giraud and Poeppel [73] reported that although individuals with dyslexia might not show the typical left-hemisphere specialization for the γ rate, the θ and low and high γ activity appeared strongly left dominant. On the other hand, there were studies which investigated the δ/θ range in participants with dyslexia without finding any differences either when using EEG-ASSR at 4 Hz [74], or when exploring MEG-ASSRs at 2, 4, 10 and 20 Hz [75].

Several methods have been proposed in order to measure EEG signals in several populations through Brain Computer Interface (BCI). A typical BCI system consists of a signal acquisition device and a signal processing device. A BCI system is generally divided in two phases. In the first phase (offline), the system is calibrated and a training algorithm with prerecorded data occurs. In the first phase, features are calculated from the prerecorded data and the optimal ones are used to train the classifier. During the second phase (online), the system recognizes in real-time brain activity patterns for a given task usually acquired by a wired or a portable sensory device. The recognition is performed with the provided knowledge from the offline training phase. For the offline training phase, several methods for automated dyslexia detection have been evaluated in dataset from different research studies. One such device is the lightweight Emotiv EPOC + wireless EEG system which has received the most empirical attention in a spectrum of different fields [76-79]. Badcock and colleagues [76,77] demonstrated that the Emotiv system could be used to acquire discernible ERP waves that are comparable to those from research-quality EEG systems.

Concerning the exploration of the relationship between several forms of learning difficulties and EEG abnormalities there have been just a handful of research using the Emotiv EPOC, mainly a Turkish research team under the supervision of Prof. Eroglou [80]. In a series of experiments, when he compared the Multiscale entropy analysis of a group with dyslexia (N = 16) to that of a typically developing group (N = 20) and having administered neurofeedback sessions with the Auto Train Brain, he found that the group with dyslexia showed significantly lower complexity at the lowest temporal scale and at the medium temporal scales than did the typically developing group.

Researchers have deployed a number of Machine Learning Classifiers to detect brain patterns specific to dyslexia. Andreadis et al. [81] used approximate entropy of EEG signals by implementing a Support Vector Machine (SVM) offering promising results with a sensitivity of 89.47% and specificity of 57.89%. Similarly, Frid and Breznitz [82] developed an effective algorithm to analyze and classify the subjects as either regular or readers with dyslexia, by using EEG recorded channels with ERP methodology during an auditory, short non-linguistic, sub-phonetic choices reaction time task, resulting in sensitivity of 68.6% and specificity of 78.2%. In a recent research, Rezvani et al. [83] also employed an SVM to assure the performance suitability of the classifier, resulting in 95% accuracy of classification of children based on local network features from different frequency bands, thus rendering the classification techniques applied to EEG graph measures both robust and reliable in distinguishing between typical and readers with dyslexia. In a review of EEG-based pattern classification frameworks for dyslexia, Perrera et al. [69] have identified the advantages and disadvantages of an EEG approach, in addition to recommending optimization methods for a better prediction of dyslexia. It is, thus, evident that several studies provide support for the use of machine learning in anatomical brain imaging when it comes to classifying population with or without dyslexia [84,85].

A broadly utilized classifier in separating individuals with dyslexia from normal readers is Random Forest, which consists of an ensemble of randomized decision trees [86]. Researchers analyzing eye-movement data achieved a high general accuracy of 89.8% [87,88] and albeit a lower one (75.9%) when it came to detecting subjects with dyslexia [88]. Plonski et. al. [89] investigated grey matter disruptions in children with dyslexia and achieved above chance accuracy (65%) after principled feature selection and assessment of classification algorithm accuracy. Other recent studies reached 100% in accuracy, sensitivity, specificity and precision for dyslexia subjects and also overall category in classifying normal and dyslexia subjects [90]. Iwabuchi et al. [91] analyzed the data by Decision tree and Random Forest, showing that machine learning regression technique had better prediction than the ordinary rule-based decision. The validity of this specific classifier was also evident in Rauschenberger's et al. [92] prototype study with 313 children (116 with dyslexia), which predicted the risk of having dyslexia before acquiring reading skills with an accuracy of 0.74 for German and 0.69 for Spanish. The prototype was designed to observe participants listening to music (via a web app), with different acoustic parameters such as frequency and duration, which relate with perceptual parameters such as pitch and loudness.

Although the perception of musical elements in relation to dyslexic reading has not been extensively studied yet, its findings are often contradictory and conflicting [93,94]. A number of studies indicate that there are more benefits to listening to classical music while executing a cognitive task, a phenomenon known as the Mozart effect [95] than other types of music [96].

In this paper a classification of university students with and without dyslexia is attempted. EEG recordings from university students with dyslexia are analyzed along with the EEG data from typically developed, age matched individuals. The use of a BCI Device is employed to validate the application of such a device in detecting (classifying) dyslexia in a higher education population. The features from the time domains are extracted, forming the feature vector to train several classifiers for nine different brain Regions of Interest (RoI). The levels of accuracy were calculated for the experimental conditions of audio recognition and visual discrimination of words based on the magnocellular deficit hypothesis following similar studies investigating the relationship of magnocellular dysfunctions with audiovisual deficits of people with dyslexia [97,98]. In order to further investigate the inhibitory or reinforcing role of classical music while executing a cognitive task, a third experimental condition of visual discrimination of words with the accompaniment of background music was added. To the best of our knowledge, this is the first comprehensive study with university students with dyslexia examining a variety of features over various experimental conditions and showing such a high classification accuracy.

The manuscript is divided into five parts. Following the Introduction, section two (Methodology) describes the database and the interactive linguistic application along with the data acquisition and EEG extraction features. The third section presents the obtained results regarding the classification model, and the fourth section discusses the main findings of the study along with the limitations of it. The last section underscores the importance of this classification method in comparison to related studies.

3. Materials and methods

The proposed methodology consists of two stages. First, the EEG signals are recorded with a wearable EEG device from 26 participants, then spectral features are calculated from each recording forming the feature vector to train a Random Forests classifier. An illustration of the proposed system is presented in Fig. 1.

3.1. Participant description

In this study, 26 right-handed university students studying in the University of Ioannina, Greece, participated in this experiment as part of a greater research investigating the contribution of magnocellular theory to the interpretation of the causal factors in dyslexia [99]. Performance was evaluated with a novel interactive application measuring audiovisual recognition and discrimination of words in three experimental conditions. The participants formed two groups with regard to whether they present learning difficulties or not. Twelve students (6 females and 6 males) were diagnosed with dyslexia, whereas 14 subjects formed the control group (10 females and 4 males). All the 12 subjects with dyslexia had undergone intervention at young age and no dyslexia-related comorbidities have been reported. Participants among the groups had approximately the same age and the average age for the group with dyslexia was 21.58 y/o and for the control group 20.93 y/o. The education level for each participant was recorded and it was the same, since all participants were university students. Written consent forms to participate in this study were obtained for all the participating subjects.

3.2. Interactive Linguistic Software Tool description

The application monitors the participants' responses on three experimental conditions, namely (a) audio recognition, (b) visual discrimination, and (c) visual discrimination with the accompaniment of background music. The material presented in the three conditions followed several predefined phonological and morphological criteria based on commonly made mistakes in Greek language by individuals with dyslexia, especially focusing on confusion of letters with visual (κ, γ, χ) or acoustic similarity (f, v, θ, ð) [100]. Specifically, in every condition the participants had to choose the correct word among a group of three words (1 real Greek word and 2 pseudowords). The average time for each response was 8.5 s.

In the first experimental condition the participants were asked to differentiate verbally presented, similar acoustic stimuli (e.g. fo´vame, fo´ðame, fo´θame). They would see 3 boxes on the screen with respective numbers and had to choose the number which corresponded to the

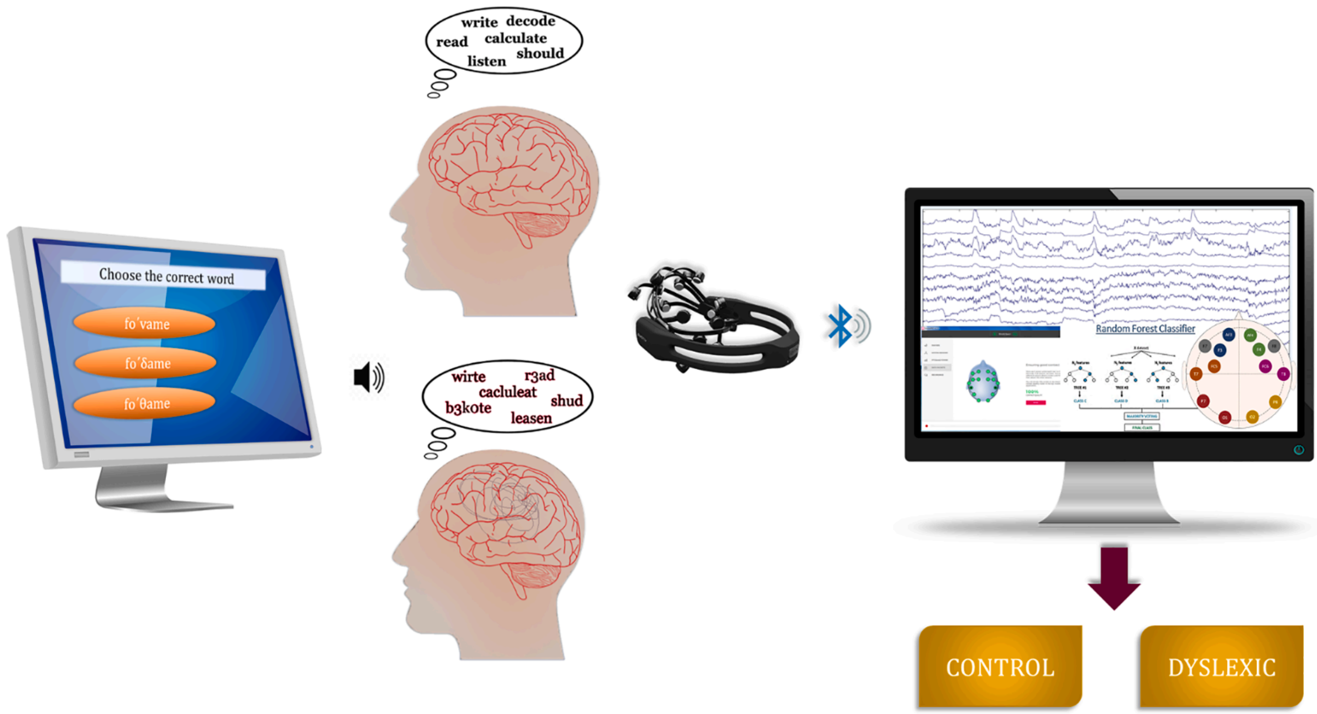

Fig. 1. An illustration of the proposed system.

correct word. In the second experimental condition, the subjects were told that they would see different words on the screen and were instructed to read them as carefully as possible and choose the one that seemed right to them. Again, the non-words contained mistakes concerning the position and the order of the letters, like sequential (fridge – frigde), insertion (computer – compluter), omission (bicycle – bicyle), or letter substitution errors (dog – tog). Finally, the third experimental condition was similar to the second one, with the difference being the simultaneous presence of musical accompaniment. The musical excerpt selected for the experiment was the Sonata for Two Pianos in D major, K. 448, a work composed by Mozart.

3.3. Data acquisition

The EEG recordings were performed in a sound- and light-attenuated room and were obtained for each subject while the evaluation test was ongoing. Before the procedure, an experienced researcher informed the participants about the experimental protocol. For each participant a 4–7 min training was needed in order to understand the protocol and became familiar with the device. During the evaluation and the EEG recording, participants were in an upright seated position, calm, in a resting state with their eyes open. The duration of each EEG recording ranged between 21 and 38 min (28 min on average), depending on the time needed for each subject to complete the test. The recording was terminated as soon as a participant felt any discomfort with the device or the procedure. In total, 5 h and 51 min of EEG recordings from subjects with dyslexia and 5 h and 47 min from subjects without dyslexia were collected, forming a database of approximately 11.5 h.

For the recordings, the Emotiv EPOC + was used, a commercial wearable EEG device. The Emotiv EPOC + is one of the most widely used sensory EEG devices for lifestyle purposes, consisting of 14 sensors with corresponding felt pads placed in the scalp according to the International 10–20 System (AF3, F3, F7, FC5, T7, P7, O1, AF4, F4, F8, FC6, T8, P8 and O2). Two additional rubber electrodes were placed in the mastoids, serving as reference channels. The sampling frequency is 128 Hz and the connection between the electrodes and the scalp is established using saline liquid solution, applied on all felt pads of each sensor. The device was set up according to the instructions provided by the EmotivPRO Software and the quality of the connectivity was regularly checked both in the beginning and during the recording.

3.4. EEG signals preprocessing

The recordings were performed with the montage according to the linked mastoids. After each recording, the EEG signals are exported in ". edf" format and processed using MATLAB platform and the EEGLAB toolbox. A Butterworth notch filter is applied to remove the 50 Hz power line noise oscillations from the EEG signals and a high-pass FIR digital filter at 0.5 Hz to remove low frequency oscillations. Then, five equiripple FIR filters are designed to allow frequencies within a certain range and attenuate frequencies outside that range. The five band-pass filters (0.5 – 4 Hz, 4 – 8 Hz, 8 – 12 Hz, 13 – 30 Hz, and 30–60 Hz) are designed with regard to the 5 EEG rhythms, attempting to extract spectral features in each frequency sub-band of interest. Then, each filtered EEG recording is segmented in non-overlapping epochs of 10 sec and spectral features are extracted from the 10-s EEG segments. Table 1 presents the sub-bands of interest with the corresponding EEG rhythms.

3.5. Feature extraction

In the literature, a variety of statistical and spectral features have been extracted for EEG analysis of brain diseases [101,102] and cognitive states [103,104]. In this study we evaluated the ability of simple spectral features, namely Energy and Shannon entropy in detecting the

Table 1
Sub-bands of interest along with the corresponding EEG rhythm.

Sub-band of Interest	EEG rhythm
0.5–4	δ
4–8	θ
8–12	α
13–30	β
30–60	γ

subtle changes in brain activations that differentiate individuals with dyslexia than those without dyslexia. Shannon Entropy measures the complexity of EEG.

More specifically, the FFT transformation is used to transform the signals from time domain to frequency domain as follows:.

$$X_j = \sum_{n=0}^{N-1} x_n \exp\left(-j\frac{2\pi}{N}ni\right) \tag{1}$$

where x_n is the signal and *Energy* is defined as:

$$Energy = \sum_{j=1}^{N} X_j^{2}, i = \delta, \theta, \alpha 1, \alpha 2, \beta 1, \beta 2, \gamma \tag{2}$$

Which is the square value of a frequency spectrum point X_j calculated for each band i.

Shannon Entropy (*ShanEn*) $= -\sum_{j=1}^{M} p_j \log(p_j)$ (2).

wherein p_j is the probability distribution of each signal x and is calculated estimating the histogram for each recording. Shannon Entropy is calculated for the entire spectrum.

3.6. Classification

The vector of spectral features was used as input to train and test a Random Forests classifier. Random Forests is an ensemble classifier, consisting of a number of decorrelated decision trees [86]. The algorithm of the Random Forest is presented with detail in Fig. 2. The prediction is performed according to the bagging method, wherein each decision tree is responsible for its own prediction, and in the end, all the decision trees vote for the most popular class [104]. Other classification algorithms, such as Support Vector Machines, Decision Trees, Naïve Bayes, k-Nearest Neighbors and Neural Networks were also tested.

The evaluation of the proposed methodology is performed on the binary classification problem "control/dyslexia", which correspond to the EEG signals obtained from 14 individuals without dyslexia (controls – CON) and 12 subjects with dyslexia (DYS). To identify unique patterns of dyslexia among different brain regions, several brain RoI are created. Specifically, the EEG information of the electrodes is grouped in pairs and clusters of electrodes, according to the electrode sites. However, due to loss of connectivity located mainly on the F8 electrode, not all EEG channels from the 26 subjects were used in the formation of RoI. Specifically, the F8 electrode was isolated and rejected and so was the corresponding channel, F7 to maintain the symmetry of the recording. Thus, the following RoI were formed (Fig. 3):

- Entire brain (AF3, F3, FC5, T7, P7, O1, AF4, F4, FC6, T8, P8 and O2)
- Left hemisphere (AF3, F3, FC5, T7, P7, O1)
- Right hemisphere (AF4, F4, FC6, T8, P8, O2)
- Left frontal (AF3, F3)
- Left temporal (T7, FC5)
- Left occipital (O1, P7)
- Right frontal (AF4, F4)
- Right temporal (T8, FC6)
- Right occipital (O2, P8)

4. Results

The performance of multiple classifiers was tested and Random Forest classifier proved to be the best in terms of accuracy. Fig. 4 represents the comparison between the accuracies of each classifier in all three conditions.

The classifier's performance is evaluated with Accuracy (ACC), Sensitivity (SENS) and Specificity (SPEC). The Accuracy of the

```
Pseudo code of Random Forests

Create k classifiers:
    for (i = 1 , i <= k , i + +):
        from training set D select data randomly with replacement, and produce D_i
        Create the root node N_i, which contains D_i
        Call Tree(N_i)
    end
Voting:
    for each instance of test set j:
        for each classifier k:
            Vote
        end
        Classify j as the majority of the k votes
    end

Tree(N):
if N consists of only one class:
    return
else:
    Randomly select a subset of possible splitting features in N
    Find the feature F with the highest information gain if split
    for each possible value cl of F:
        Create child node of N, N_cl
        Set as contents of N_cl all instances of N that the value of F is cl
        Call Tree(N_cl)
    end
end
```

Fig. 2. Random Forest Pseudo code.

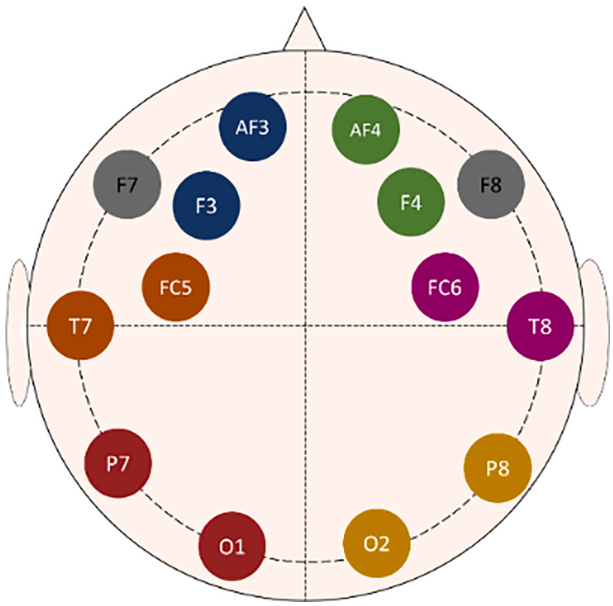

Fig. 3. Regions of Interest according to the electrode sites. (Blue: Left frontal, Orange: Left temporal, Red: Left occipital, Green: Right frontal, Purple: Right temporal, Yellow: Right occipital, Grey: Rejected channels).

classification shows the ability of the classifier to differentiate DYS cases from CON. The Sensitivity shows the percentage of DYS subjects correctly classified as having dyslexia and Specificity shows the percentage of cases correctly classified without dyslexia of all the subjects characterized as controls.

All the tested classification algorithms performed comparable, but the Random Forests were found to be the most effective. Thus, in a sample of 26 students (12 with dyslexia and 14 without), a classification performance of only Random Forests was calculated for each RoI for the whole duration of the experiment for each experimental condition.

For each RoI in the first experimental condition, where an audio recognition of words was involved (Table 2), the classification of subjects was checked. The best classification level of accuracy of 96.24% (SENS = 96.34 %, SPEC = 96.10 %) was found in the entire brain. The left hemisphere indicated the second highest value of accuracy of 93.02% (SENS = 93.37 %, SPEC = 92.58 %), followed by the right hemisphere (ACC = 92.00 %, SENS = 90.40 %, SPEC = 94.74 %). In addition, there were six RoI where the levels of accuracy ranged within the 8th decile with the lowest level of accuracy being reported in the left occipital lobe (ACC = 81.07 %, SENS = 81.02 %, SPEC = 81.14 %). More specifically, the left frontal lobe had an accuracy level of 86.98% (SENS = 89.12 %, SPEC = 84.49 %), followed by the right occipital lobe (ACC = 85.25 %, SENS = 82.89 %, SPEC = 88.84 %), the right frontal lobe (ACC = 84.48 %, SENS = 84.85 %, SPEC = 83.38 %), the right temporal lobe (ACC = 83.22 %, SENS = 81.44 %, SPEC = 85.87 %), and lastly the left temporal lobe (ACC = 82.98 %, SENS = 81.36 %, SPEC = 85.19 %). Fig. 6 represents the ROC curves of the classification performances of each brain region at condition (1).

The classification of subjects for each RoI was checked regarding the second experimental condition where the participant had to visually discriminate groups of words with phonologically similar features. The results of the classification were quite similar to the way the subjects were classified in the first experimental condition (see Table 3). The best classification level of accuracy of 95.12% (SENS = 97.34 %, SPEC =

Table 2
Classification performance of Random Forests concerning each RoI (ACC: Accuracy, SENS: Sensitivity, SPEC: Specificity) for the first Condition.

RoI	ACC (%)	SENS (%)	SPEC (%)
Entire brain	96.24 (1.66)	96.34 (1.67)	96.1 (2)
Left hemisphere	93.02 (2.7)	93.37 (2.71)	92.58 (2.82)
Right hemisphere	92.00 (2.7)	90.40 (2.73)	94.74 (3.44)
Left frontal	86.98 (3.14)	89.12 (3.14)	84.49 (3.25)
Left temporal	82.98 (3.35)	81.36 (3.36)	85.19 (3)
Left occipital	81.07 (3.6)	81.02 (3.63)	81.14 (3.71)
Right frontal	84.48 (3.27)	84.85 (3.28)	83.87 (3.78)
Right temporal	83.22 (3.79)	81.44 (3.79)	85.87 (4.09)
Right occipital	85.25 (3.58)	82.89 (3.59)	88.84 (3.89)

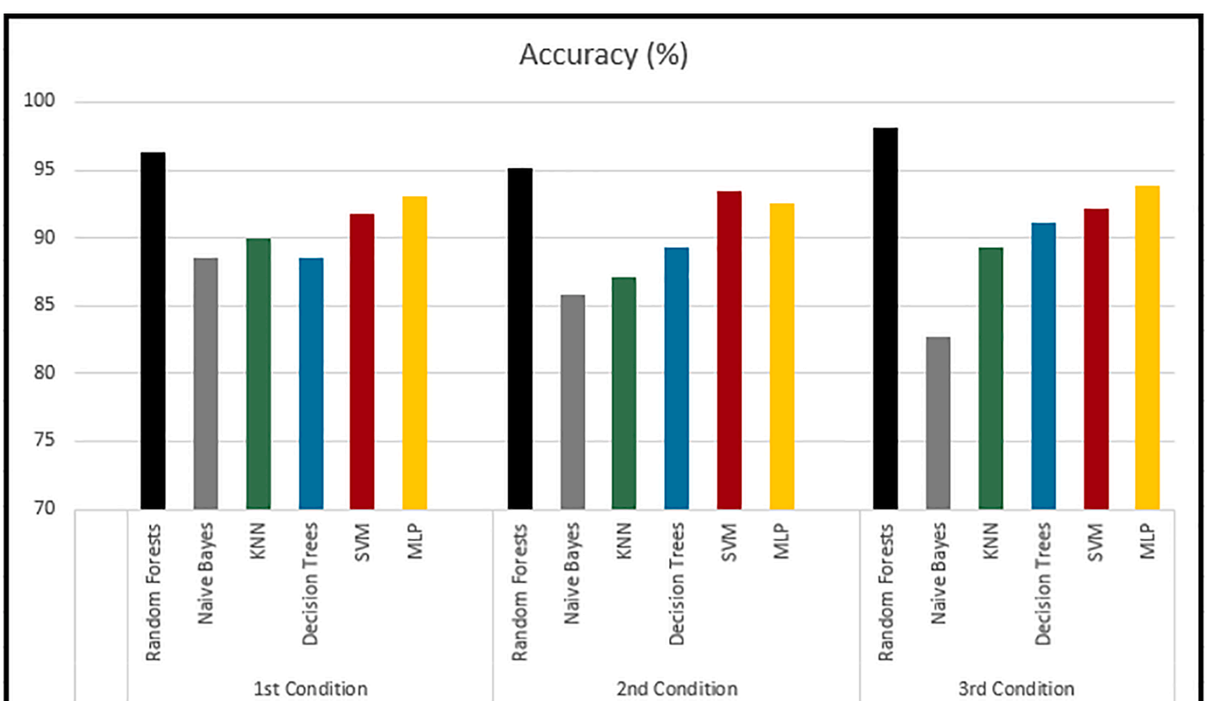

Fig. 4. Accuracy scores of every classifier at Entire Brain RoI in all three conditions.

93.08 %) was found in the entire brain, whereas the lowest level of accuracy was reported in the left occipital lobe (ACC = 79.46%, SENS = 81.00%, SPEC = 78.24%). The left hemisphere indicated the second highest value of accuracy of 93.22% (SENS = 97.04%, SPEC = 89.94%). In addition, there were six RoI where the levels of accuracy ranged within the 8th decile. More specifically, the right hemisphere reported an accuracy level of 87.25% (SENS = 86.51%, SPEC = 88.02%), followed by the left frontal lobe which had an accuracy level of 86.36% (SENS = 87.81, SPEC = 85.00%), the right occipital lobe (ACC = 83.58%, SENS = 82.19%, SPEC = 85.05%), the right frontal lobe (ACC = 83.10%, SENS = 81.36%, SPEC = 85.07%), the right temporal lobe (ACC = 81.86%, SENS = 82.82%, SPEC = 80.99%), and lastly the left temporal lobe (ACC = 81.34%, SENS = 80.58%, SPEC = 82.05%). Fig. 7 represents the ROC curves of the classification performances of each brain region at condition (2).

The Random Forests vector machine was employed to classify the subjects for each RoI to one of two categories of students with dyslexia and the ones without dyslexia who served as the control group in the experiment. The third experimental condition required from the participants to visually discriminate groups of words with the accompaniment of background music. The results of the classification did not differ greatly from the previous classifications of the whole sample and the two experimental conditions (see Table 4). Once again, the best and highest classification level of accuracy in all the calculated classifications was found in the entire brain (ACC = 98.01 %, SENS = 98.73 %, SPEC = 97.39 %). The left hemisphere indicated the second highest value of accuracy of 95.37% (SENS = 97.41 %, SPEC = 93.39 %), followed by the right hemisphere (ACC = 91.00 %, SENS = 90.75 %, SPEC = 91.23 %). In addition, all the rest RoI ranged within the 8th decile, with the right frontal lobe reporting the lowest level of accuracy (ACC = 82.83 %, SENS = 82.49 %, SPEC = 83.12 %). Unlike the previous classifications, the left occipital lobe reported the fourth highest level of accuracy of 88.19% (SENS = 90.38 %, SPEC = 86.07 %). Moreover, the right occipital lobe reported an accuracy level of 87.41% (SENS = 87.90 %, SPEC = 86.88 %), followed by the left frontal lobe which had an accuracy level of 86.02% (SENS = 89.77 %, SPEC = 82.68 %), the right temporal lobe (ACC = 85.02 %, SENS = 87.17 %, SPEC = 82.91 %), and finally, the left temporal lobe (ACC = 84.35 %, SENS = 85.27 %, SPEC = 83.40 %). Fig. 8 represents the ROC curves of the classification performances of each brain region at condition 3. Tables 2-4 represent the ACC, SENS and SPEC score along with their Standard Deviations for each experimental condition for each RoI. Fig. 5 represent the comparison between the accuracies of each condition at every RoI. Fig. 9 is summing up the results of this experiment, representing the ACC, SENS, SPEC scores for each RoI in every condition.

5. Discussion

Discrimination between dyslexia and non-dyslexia, with the use of machine learning techniques in the analysis of EEG signals, has been previously described (Table 5) in studies using different methodology in the acquisition of recordings during resting state [83,105], and/or during writing [105], or under an auditory stimulus [81,82]. Despite their significant influence on the field of brain activation in dyslexia, our study's contribution is two-fold compared to these efforts: firstly, we targeted university students with dyslexia which is a rarely examined group [82], and secondly, the employment of EEG signals in different phonological tasks presenting auditory, and visual stimuli with or without the presence of background music has never been examined before. In the proposed study, EEG recordings are acquired during listening and reading, two skills that can capture learning deficits. Results show that the proposed model provides a clear discrimination between individuals with and without dyslexia solely from quantitative EEG features. Of course, comparison of our method with other classification approaches presented in the literature cannot be straightforward, since the database, the means and the experimental protocol differ. However, it is of great scientific interest to present and discuss other proposed approaches in the field of EEG-based dyslexia analysis and shed light on the brain activity of students with learning disorders as it expressed by the EEG.

The classification of unique dyslexic patterns was achieved through EEG signals obtained from 12 individuals with dyslexia and 14 subjects without dyslexia during a non-resting state condition. Spectral features were extracted from pairs and clusters of electrodes and formed the feature vector that trained a Random Forests classifier to discriminate between "dyslexia" and "control" cases providing high performance in terms of Accuracy, Sensitivity, and Specificity, regarding different brain RoI. It is also significant to highlight that the Random Forests classifier reported high levels of accuracy (above 95%) with signals produced by a BCI device and not by a clinical grade EEG device.

The proposed EEG-based methodology showed significant results in the detection of the group of subjects with dyslexia. The best classification performance concerning the Accuracy, Sensitivity and Specificity, was acquired for the Entire brain, followed by the Left and Right hemisphere, the frontal region of the left hemisphere. This diversity of regions likely reflects complex patterns of dysfunction of a set of neural networks of regions involved in either phonological or morphological word processing by individuals with dyslexia [106,107].

Regarding the first experimental condition where the subjects had to respond to auditory stimuli, the Random Forests classifier reported high levels of accuracy, thus confirming the heterogeneity of rhythm activation in different regions between the two groups of the sample [108]. More specifically, higher activation was noted in the left temporal region, which is the main neural region responsible for sound-based phonological representations [109], demonstrating the difficulty of individuals with dyslexia to make correct auditory word discrimination. The findings are in agreement with the results of Gori et al. [34] and Kandel et al. [110], enriching the hypothesis that left temporal low activity reveals a strong interaction between auditory processing difficulties and reading impairments. Similar findings provide neurobiological evidence of underlying nervous system dysfunction in posterior regions of the brain, including the parieto-temporal region and the temporo-occipital region [111]. These atypical abnormalities in the left temporo-occipital region of the brain may play an important role in

Table 3
Classification performance of Random Forests concerning each RoI (ACC: Accuracy, SENS: Sensitivity, SPEC: Specificity) for the second Condition.

RoI	ACC (%)	SENS (%)	SPEC (%)
Entire brain	95.12 (1.92)	97.34 (1.92)	93.08 (1.91)
Left hemisphere	93.22 (2.17)	97.04 (2.18)	89.94 (2.17)
Right hemisphere	87.25 (3.15)	86.51 (3.16)	88.02 (3.17)
Left frontal	86.36 (3.69)	87.81 (2.94)	85.00 (2.94)
Left temporal	81.34 (3.69)	80.58 (3.7)	82.05 (3.64)
Left occipital	79.46 (2.88)	81.00 (2.89)	78.24 (3)
Right frontal	83.10 (3)	81.36 (3)	85.07 (3.03)
Right temporal	81.86 (3.47)	82.82 (3.47)	80.99 (3.47)
Right occipital	83.58 (3.31)	82.19 (3.32)	85.05 (3.3)

Table 4
Classification performance of Random Forests concerning each RoI (ACC: Accuracy, SENS: Sensitivity, SPEC: Specificity) for the third Condition.

RoI	ACC (%)	SENS (%)	SPEC (%)
Entire brain	98.01 (1.53)	98.73 (1.53)	97.39 (1.62)
Left hemisphere	95.37 (2.18)	97.41 (2.18)	93.39 (2.14)
Right hemisphere	91.00 (2.81)	90.75 (2.81)	91.23 (2.84)
Left frontal	86.02 (3.54)	89.77 (3.54)	82.68 (3.46)
Left temporal	84.35 (3.26)	85.27 (3.26)	83.40 (3.25)
Left occipital	88.19 (2.87)	90.38 (2.88)	86.07 (2.9)
Right frontal	82.83 (3.39)	82.49 (3.4)	83.12 (3.53)
Right temporal	85.02 (3.4)	87.17 (3.4)	82.91 (3.37)
Right occipital	87.41 (2.88)	87.90 (2.89)	86.88 (2.89)

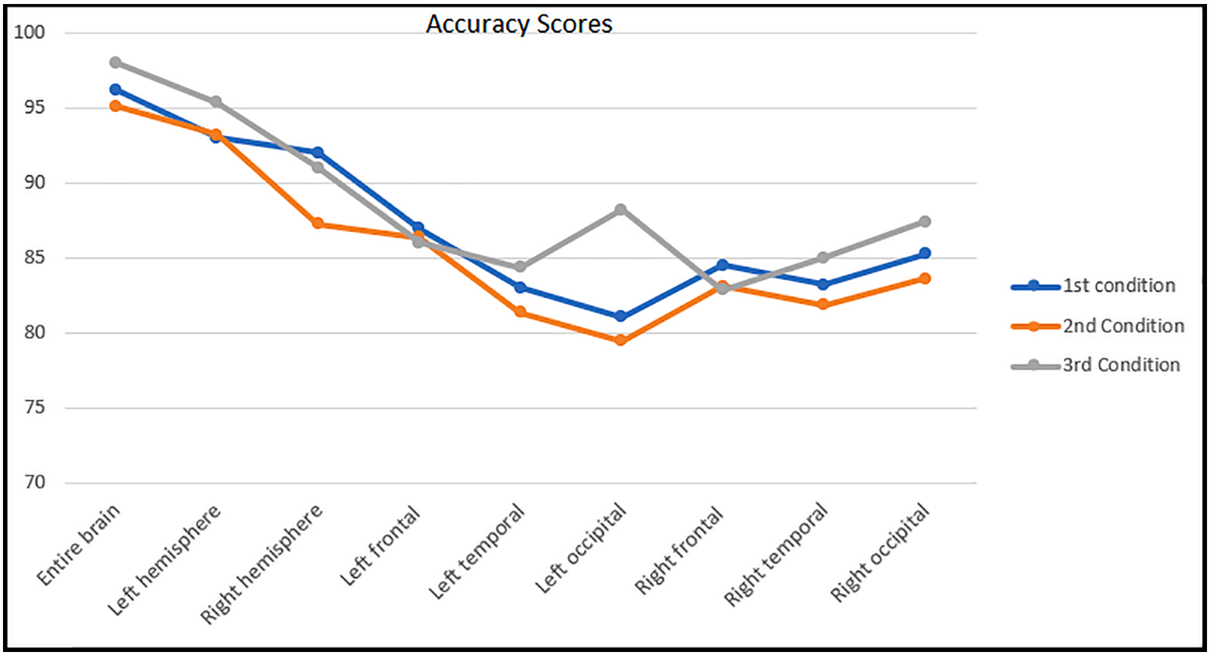

Fig. 5. Comparison of Accuracy scores of each condition for each RoI.

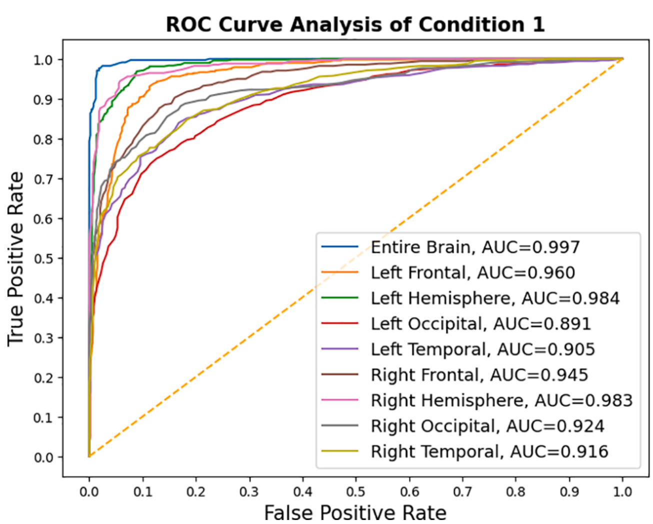

Fig. 6. Roc Curve of Classification Performances in Different Brain Regions at Condition (1).

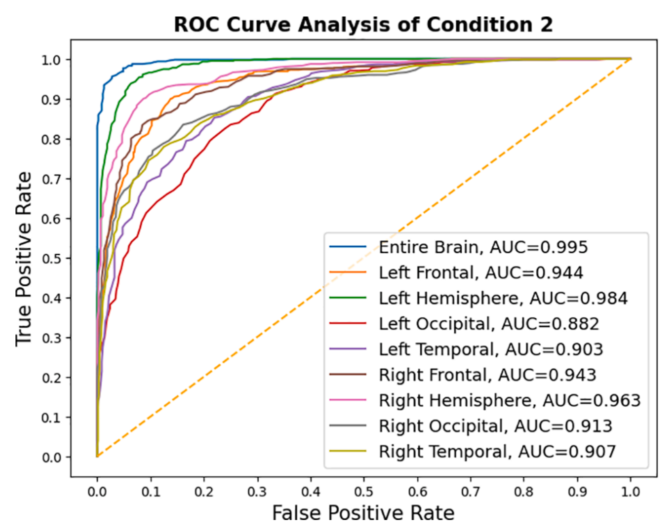

Fig. 7. Roc Curve of Classification Performances in Different Brain Regions at Condition (2).

word recognition and the integration of phonological processes [112], as well as support impaired phonological awareness in individuals with dyslexia [43].

The second experimental condition, where the subjects responded in visual stimuli, reported high levels of accuracy in the classification of subjects with and without dyslexia, revealing differences in the activation of the occipital and parietal regions of the right and left hemispheres. Importantly, this finding confirms similar studies where motor and sensory information differentiation between the two hemispheres was observed in people with dyslexia [43]. These developmental changes or asymmetries in the neural network of brain structures may form the basis for explaining sensory and cognitive problems in dyslexia. Similar findings of underactivation in the left parietal lobe were reported in similar studies in children with dyslexia during phonological awareness tests [7,111]. Furthermore, the differences in the parieto-occipital regions are consistent with findings from similar EEG studies between individuals with dyslexia and control groups [113].

Finally, the best classification performance compared to the two previous conditions was achieved when participants had to visually discriminate groups of words with the accompaniment of background music. This characteristic finding may indicate that the presence of the musical stimulus plays a crucial role in the greater activation of the right frontal, temporal, and parietal regions in students with dyslexia in an attempt to cope with the cognitive demands of the task. At the same time, the lower activation of the parietal region likely demonstrates the contribution of the specific musical Mozart excerpt to the alertness and brain stimulation during cognitive function [114]. A study aimed at determining the effect of Mozart's music on brain activity found that people who listened to Mozart had less brain activity and performed better when given cognitive tests [115]. This is partly explained by the fact that the right temporal cortex is responsible for planning complex cognitive behaviour and helps in decision making [116]. However, most of these reports [117] only present the effect of Mozart music in a typical adult population [114,118], without investigating this effect on the CNS

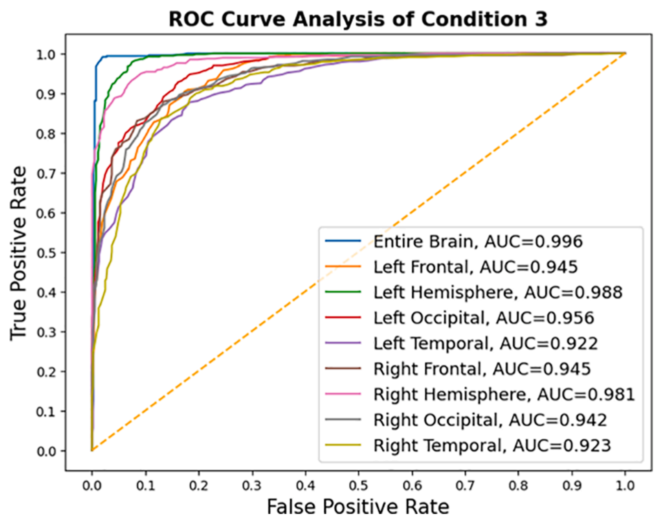

Fig. 8. Roc Curve of Classification Performances in Different Brain Regions at Condition 3.

in adults with dyslexia.

The Emotiv EPOC+, a commercial EEG wearable device was evaluated presenting good discrimination results. The proposed study shows the ability of such a lifestyle device to capture adequately the differences in brain dynamics among healthy young adults and age-matched subjects with learning disorders. To the best of our knowledge, this is the first time a sophisticated, light-weighted and wearable device is used to record EEG signals aiming to analyze dyslexia-related RoI. In a recent conference paper, Gunet Eroglu et al. [80] utilized Emotiv EPOC + and designed a neurofeedback mobile app in an attempt to improve cognitive functions in children with dyslexia. In the literature, Zainnudin et al. [105] also utilized a restrained number of electrodes and a good classification outcome was obtained. However, results of the proposed study cannot be directly compared with this study since brain activations differ among children and adults. Furthermore, it should be taken into consideration the fact that the adults follow long-term intervention programs, even from the preschool age.

Despite several statistically significant results which revealed generally high levels of accuracy concerning the correct classification of the two groups of subjects, there were some limitations in this study worth mentioning. Firstly, although the sample of the study consisted of a relatively small number of subjects (12 students with dyslexia and 14 controls), it has to be argued that in medical research the number of

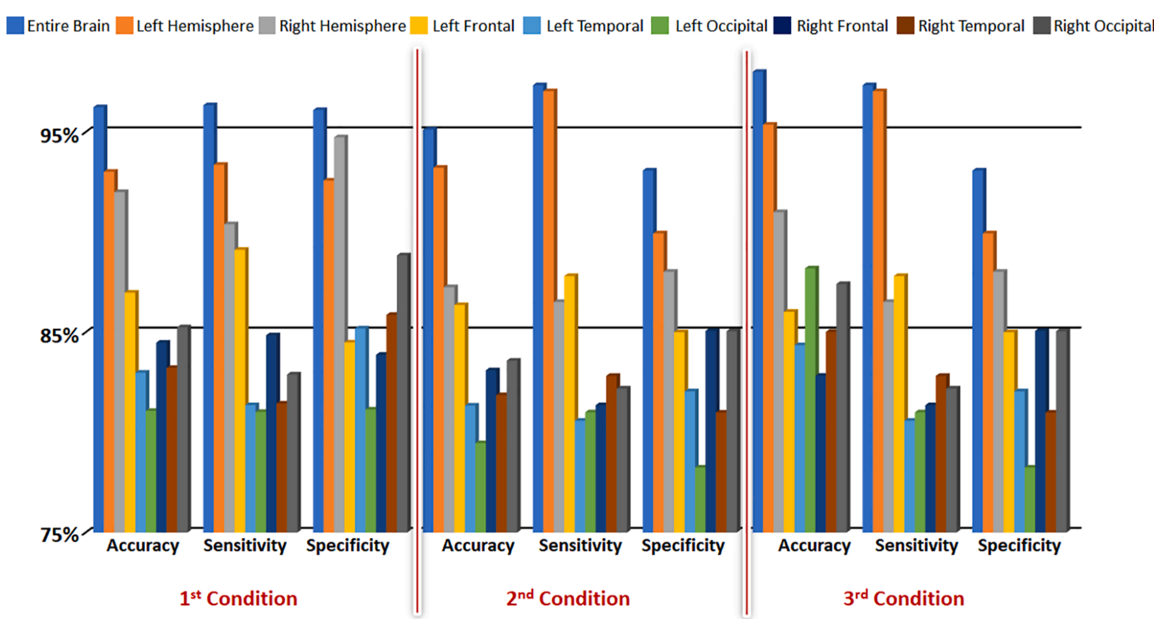

Fig. 9. ACC, SENS, SPEC scores for every RoI in every condition.

Table 5
A representation of the most recent EEG-based studies related to dyslexia.

Author	Database (DYS/CN)	Recording Status	EEG Duration	Age (years)	No. of Electrodes	Methodology	Results (%)		SPEC
							ACC	SENS	
Andreadis *et al. (2009)* [81]	38/19	auditory stimulus	500 ms before/after stimuli	2–13	15	Approximate Entropy, SVM	Not reported	89.47	59.87
Frid & Breznitz (2012) [82]	20/30	auditory stimulus	200 ms before stimuli	24–40	64	Positive Area (Ap), Spectral Flatness Measure, statistical features and Power Spectral Density, SVM	84.60	Not reported	
Rezvani *et al. (2019).* [83]	29/15	resting state	2 min	8	64	37 features from graphs, SVM (linear)	95.56	Not reported	
Zainuddin *et al. (2016)* [105]	20/10	resting state, writing	Not reported	7–12	8	DWT, coefficient of β and ratio θ/β, ELM	89.00	Not reported	
This work	12/14	auditory, visual, visual with background music	28 min	19–26	12	filtering, Energy *δ, θ, α1, α2, β1, β2, γ*, Shannon Entropy, Random Forests	87.04	90.91	80.95

subjects is most limited [69]. In addition, even though there are no sufficient studies using adults' subjects with dyslexia, the sample size was consistent with studies using similar classification methodology [119]. Secondly, the categorization of the participants into two groups (Control and Students with Dyslexia) was established on a previous formal diagnosis of their reading and writing difficulties, while one clear difference between students of a university and other young people with dyslexia was that students have received more long-term training than other young people in all kinds of language-related and other cognitive abilities. However, the classification performed in this study, provided quite good results for their dyslexia patterns' identification, underling thus the continuity of their learning difficulties. Finally, a major issue we had to deal with was the electrodes' detachment during recording. Even though the connectivity was checked regularly during the experiments, the spatial information had to be reduced; however, classification performance is sufficient. Results showed that even with a rather small number of channels from the occipital/parietal region dyslexia can be detected with an accuracy of approximately 70%.

6. Conclusion

In summary, this is the first report examining a variety of features over different experimental conditions with a high classification accuracy that results in correct discrimination between higher education students with and without dyslexia. The proposed method combines a non-invasive BCI device which is less costly (than usually clinical cases) and causes minimal discomfort and a linguistic software tool that enhances the interaction capabilities of the subjects, thus encouraging more dyslectic people to participate in our research. Our main goal is to enrich our EEG dyslexic database by performing early screening of the population in a costless way offering optimizations through the findings to assist future research in dyslexia prognosis.

Institutional Review Board Statement.

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Ethics Committee of University of Ioannina (1358/04–11-2016).

Informed Consent Statement.

Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the participants to publish this paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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