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Research Article

Classification of Intensive-less Intensive and Related-Unrelated Tasks

Mustafa Turan ARSLAN[1,*] , Esen YILDIRIM[2]

[1]Kırıkhan Vocational School, Hatay Mustafa Kemal University, Hatay, Turkey.
***Corresponding Author: Email:** mustafaturanarslan@gmail.com - **ORCID**: 0000-0001-5498-6571

[2] Department of Artificial Intelligence Engineering, Faculty of Computer and Informatics, Adana Alparslan Türkeş Science and Technology University , Adana, Turkey
Email: eyildirim@atu.edu.tr - **ORCID**: 0000-0003-3484-3965

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Abstract:

This study investigates the classification of electrical brain activity during intensive-less intensive and related-unrelated tasks. EEG signals were collected from 20 physically and mentally healthy university students (15 males, 5 females) residing in Adana and Hatay, Turkey, through 14 channels. Continuous Wavelet Transform analysis was applied for feature extraction. Subsequently, subject-dependent and subject-independent classifications were performed using the k-nearest Neighbour algorithm. In subject-dependent classification, the accuracy range for intensive-less intensive tasks varied between 77.6% and 89.8%, while the range for related-unrelated tasks was between 73.2% and 88%. Subject-independent classification yielded an accuracy of 79.2% for intensive-less intensive tasks and 77.5% for related–unrelated tasks.

1. Introduction

The brain, a vital organ, orchestrates its functions through the generation of electrical signals during various activities. These electroencephalographic (EEG) signals, measured by dedicated devices, can be captured and stored using specialized software. Analysis of EEG data focuses on several key parameters: time of occurrence, amplitude, and frequency. However, due to their inherent high dimensionality and non-stationary nature [1], classical signal processing techniques like the Fourier Transform, which assumes signal stationarity within a window, are insufficient for EEG analysis. Consequently, multiresolution analysis techniques, such as Wavelet Transform, have emerged as powerful tools for EEG signal processing [2-4]. A multitude of studies have employed Continuous Wavelet Transform (CWT) in conjunction with various classification algorithms for the analysis of EEG signals [5, 6]. Eraldemir et al. [7] investigated the influence of city noise and popular music environments on EEG signals during problem-solving tasks with varying difficulty levels (simple and hard) utilizing the Cognitive Tasks Database in Different Environments. CWT was employed to extract features from EEG data acquired from 17 undergraduate and postgraduate students while they engaged in solving both simple and hard questions. Subsequently, a Bayesian network classifier was implemented to categorize the EEG signals recorded under city noise and popular music conditions while participants solved simple and hard questions. The results revealed high classification accuracies, achieving 90.10% and 93.92% for simple and hard questions, respectively. These findings suggest that EEG data collected in diverse environments, including noise and preferred music, can be classified with high accuracy during problem-solving tasks, with a notable increase in successful classification for tasks of higher difficulty. Mao et al. [8] proposed a novel approach for emotion classification in EEG signals. By employing spectral analysis, they transformed the discrete EEG signals into a time-frequency representation. Their approach leveraged the wavelet transform to generate scalogram images of the EEG signals, which capture the time-localized energy distribution of the signal. Subsequently, convolutional neural networks (CNNs) were utilized for feature extraction from the scalograms. Two classification models were proposed based on the number of target emotions: one model distinguishes four basic emotions using

predefined threshold values, while the other model differentiates eight emotions. Data augmentation techniques were employed to effectively expand the dataset size to address the challenge of class imbalance introduced by the second model. The performance of the proposed models was evaluated using various metrics and compared against existing methods reported in the literature. Shukla et al. [9] proposed an automated algorithm for seizure detection utilizing a combination of CWT and CNNs. This approach classifies seizure and non-seizure events within the University of Bonn Germany dataset. To enhance the training efficiency of the deep learning classifier, data augmentation techniques were employed to effectively expand the dataset size. Subsequently, the EEG data was segmented into windows, and CWT was applied to each segment to generate scalogram plots. These scalogram image representations were then used to train the CNN model for seizure classification. The influence of various window sizes (1 second, 2 seconds, and 3 seconds) on classification accuracy was investigated, revealing that 3-second window segments yielded the optimal performance on both the original and augmented datasets.
The classification of EEG signals acquired during cognitive tasks has emerged as a prominent area of research in recent years. Kottaimalai et al. [10] pioneered the application of Principal Component Analysis (PCA) to EEG data. This technique aimed to reduce the dimensionality of feature vectors, facilitating subsequent classification using Artificial Neural Networks (ANNs). Notably, they reported achieving 100% accuracy in their classification task. Amin et al. [11] employed the Discrete Wavelet Transform (DWT) method to extract features from EEG signals acquired from eight healthy male volunteers at Petronas Technology University. The extracted feature vectors were subsequently classified using various machine learning algorithms, including Support Vector Machines (SVM), Multilayer Perceptron (MLP), k-nearest Neighbors (k-NN), and Naive Bayes (NB). Feature extraction relied on the calculation of total and relative sub-band energies from the A4 approximation coefficient and D1-D4 detail coefficients. The results revealed that the extracted features achieved classification accuracies exceeding 98% using both SVM and MLP classifiers. Notably, SVM and MLP achieved classification accuracies exceeding 98% when utilizing features extracted from the A4 and D4 sub-bands. Erhan et al. [12] investigated the differentiation in mental arithmetic activity performance using electroencephalogram (EEG) and electrocardiogram (ECG) signals. Participants (n = 36) engaged in arithmetic tasks, and their EEG and ECG recordings were classified as "good" or "bad" performance based on the number of procedures completed within a set time frame. The EEG signals, acquired from 19 channels, were segmented into 10-second epochs. Subsequently, wavelet transform was applied to both the segmented EEG and ECG recordings to extract sub-components. Feature extraction for EEG involved calculating the energy of the wavelet components. The resulting feature set was then classified using logistic regression, SVM, linear discriminant analysis (LDA), and k-NN. This feature extraction process was repeated for the ECG signals, leading to an expanded feature set. The classification process in this expanded feature space was performed again using the same aforementioned classifiers. Analysis revealed that wavelet-based features effectively discriminated between good and bad mental arithmetic performance. High classification accuracy was achieved, with k-NN and SVM yielding the best results (97.22% and above). Notably, combining features from both EEG and ECG signals increased classification accuracy compared to using EEG alone (k-NN reaching 99% accuracy).

In this study, EEG signals gathered during a slideshow consisting of related-unrelated tasks and intensive-less intensive tasks, were classified using the k-NN algorithm. Features for classification are extracted using the CWT methodology. Both subject-dependent and subject-independent classification performances are presented. The remainder of the paper is structured as follows: Section 2 provides a brief overview of the EEG data collection, feature extraction, and classification algorithm. Section 3 presents the classification results achieved with k-NN, and the conclusion is provided in Section 4.

2. Materials and methods

The primary steps utilized in the study are outlined in Fig. 1.

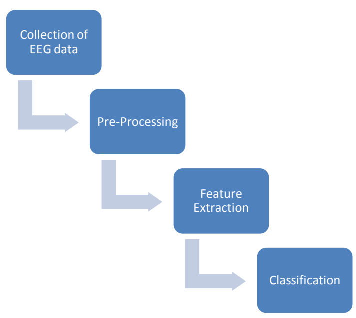

Figure 1. *The fundamental steps of the experimental study*

2.1 Database Collection

In this study, the original database with a focus on maximum attention was constructed to examine attention-oriented tasks. The research was conducted in strict adherence to ethical principles and received approval from the Hatay Mustafa Kemal University Hospital Research Ethics Committee (Number and No: 25.03.2021/03-2021/24). All participants provided written informed consent, following the ethical guidelines of the Declaration of Helsinki. The task involved counting the number of target objects among various objects arranged side by side in a 10 by 10 matrix. The number of target objects and their relation to non-target objects varied, creating four distinct tasks: related-intensive, related-less intensive, unrelated-intensive, and unrelated-less intensive. "Intensive/less intensive" refers to the density of target images, while "related/unrelated" indicates the relationship between target and non-target images. For example, a related-intensive task would have at least one-third of the images as target images, with non-target images being related to the target (e.g., if the target is an apple, non-target images could be an orange, a pear, or a banana). Conversely, an unrelated-less intensive task would also have at least one-third of the images as target images, but the non-target images would be unrelated to the target (e.g., if the target is a rabbit, non-target images could be an orange, a red apple, or a green apple). EEG recordings were conducted in three sessions, each comprising 12 tasks, resulting in a total of 36 tasks per participant. Each session took approximately 45 minutes to complete, and EEG data was collected on different days for each participant.

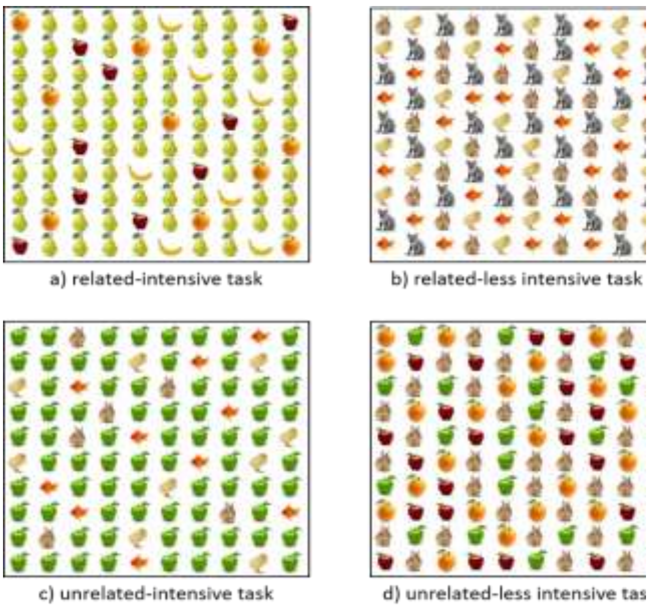

Figure 2. *The different task samples*

Examples of the four different tasks are shown in Fig. 2. The EEG data used in this study was collected from a volunteer pool of twenty healthy university students (15 male, 5 female) aged between 25 and 42 years (33 ± 5.41 years) residing in Turkey. All participants reported normal physical and mental health with no history of psychiatric or neurological disorders. They were native Turkish speakers with unimpaired cognition, attention, and sensory function. Table 1 presents the participants' consumption habits of tea, coffee, cigarettes, and alcohol.

Table 1. *Participants' Habits*

[a]P	[b]TC	[c]CC	[d]S	[e]AC
1	Rarely	Frequently	Yes	No
2	Rarely	Frequently	No	No
3	Rarely	Rarely	No	No
4	Rarely	Rarely	No	No
5	Rarely	No	Yes	No
6	Frequently	Frequently	No	Rarely
7	Frequently	Frequently	Yes	No
8	Frequently	Frequently	No	No
9	Frequently	Frequently	No	No
10	Frequently	Frequently	No	No
11	Frequently	Frequently	No	No
12	Frequently	Rarely	No	No
13	Frequently	Frequently	Yes	No
14	No	Rarely	No	Rarely
15	Rarely	Frequently	No	No
16	Frequently	Frequently	No	Rarely
17	Frequently	Rarely	Yes	No
18	Rarely	Rarely	No	No
19	Frequently	Rarely	No	No
20	Frequently	Frequently	No	No

[a]Participant: **P;** [b]Tea Consumption: **TC;** [c]Coffee Consumption: **CC**; [d]Smoking: **S;** [e]Alcohol Consumption: **AC**

Participation was voluntary and uncompensated. After providing written informed consent, participants were briefed on the experimental procedures. They were instructed to focus solely on counting target objects presented on each visual stimulus and verbally report the count afterwards. EEG signals were recorded using a wireless and portable Emotiv EPOC+ device. This device comprises 14 electrodes positioned according to the international 10-20 system, capturing activity from 14 scalp locations (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4) simultaneously at a sampling rate of 128 Hz. Additionally, the Emotiv EPOC+ includes two reference electrodes (P3 and P4) designated as CMS/DRL.

To minimize artifacts in the EEG signals, participants were instructed to refrain from excessive muscle movements, blinking, and swallowing before the recording sessions. EEG recordings were conducted in a controlled environment designed to minimize attention lapses during the experiment. This environment ensured serenity, comfort, adequate lighting, and minimal noise. Fig. 3 presents a sample image from the EEG recording session.

Figure 3. *The position of the EEG device on the scalp and test environment*

The EEG recording was synchronized with the presentation of the slides on the computer screen. Additionally, participants' responses were time-stamped using the same interface. Each session included a baseline correction and a demonstration of the target, each lasting 5 seconds. The duration of each task slide was set to 35 seconds. After each response, participants had a 10-second rest period during which they indicated the number of targets they counted. The experimental protocol for each session is illustrated in Fig. 4.

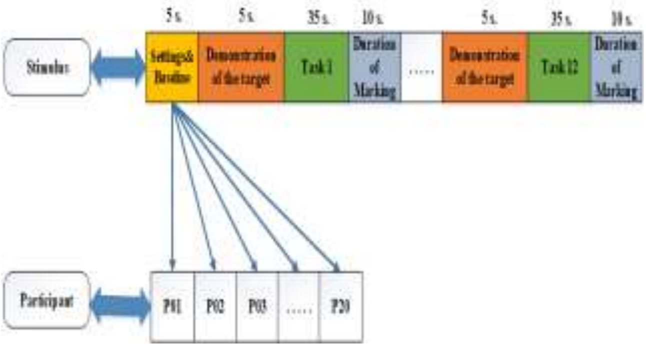

Figure 4. *Experimental protocol*

2.2 Pre-Processing

Initially, a Butterworth band-pass filter was applied to the EEG data, with a focus on frequencies between 1 Hz and 45 Hz. The EEG data, gathered from each participant across multiple sessions, was then segmented into 12 tasks, each lasting 35 seconds. This process resulted in a total of 720 tasks. Subsequently, we employed Independent Component Analysis (ICA) on the raw signals to eliminate non-brain activity signals, such as eye blinks, lateral eye movements, and heartbeat-related artifacts.

2.3 Feature Extraction

In this study, the filtered EEG signals were divided into 2-second segments with 50% overlap and windowed using a rectangular window. The spectral power of each windowed segment was then computed using CWT across four frequency bands: theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30 Hz-45 Hz).

The selection of particular wavelet function is indeed contingent upon the desired features to be extracted from the signal and the inherent characteristics of the signal itself [13]. The literature offers a vast array of mother wavelet functions, including Daubechies, Coiflet, Morlet, Gaussian, Symlet, Mexican Hat, Haar, and Biorthogonal wavelets. However, employing Morlet wavelets for the detection of rhythmic activity within EEG signals is a well-established and prevalent technique in both signal processing and neuroscience domains [14-18]. Consequently, 56 features encompassing theta, alpha, beta, and gamma energy bands were extracted from 14 EEG channels using a Morlet wavelet in this study.

2.4 Classification

Cognitive tasks were utilized to collect EEG signals, which were then classified using the k-NN algorithm. k-NN is an influential supervised machine learning technique utilized for classifying and enhancing existing data through mathematical and statistical methodologies. Additionally, k nearest neighbor stands out as one of the most extensively applied theoretical and straightforward classification methods due to its straightforward implementation and the effectiveness of its learning process [19].

3. Results and Discussion

This study investigated the influence of the CWT and k-NN method on classification performance, motivated by the hypothesis that CWT-derived features yield superior classification accuracy. Features were first extracted from the signals using the CWT and then categorized as corresponding to either intensive-less intensive or related-unrelated tasks. k-NN algorithm was employed to achieve binary classification of the EEG signals. The 10-fold cross-validation method was employed to assess the performance of the k-NN algorithm.

Classification performance was evaluated using both subject-dependent and subject-independent approaches. The results for subject-dependent analyses are presented in Table 2 and Table 3, for intensive-less intensive and related-unrelated binary task classifications, respectively. The average results of the subject-dependent experiment are given in Table 4.

Table 2. *The results of subject-dependent for intensive-less intensive binary task classification*

[a]P	[b]A	[c]Pr	[d]R	[e]F	[f]ROC
1	0.795	0.795	0.795	0.795	0.788
2	0.898	0.899	0.898	0.898	0.900
3	0.863	0.863	0.863	0.863	0.873
4	0.783	0.783	0.783	0.783	0.783
5	0.776	0.776	0.776	0.776	0.771
6	0.802	0.802	0.802	0.802	0.81
7	0.849	0.849	0.849	0.849	0.852
8	0.787	0.788	0.787	0.787	0.777
9	0.786	0.786	0.786	0.786	0.785
10	0.872	0.872	0.872	0.872	0.862
11	0.804	0.805	0.804	0.804	0.804
12	0.863	0.863	0.863	0.863	0.876
13	0.876	0.876	0.876	0.876	0.88
14	0.863	0.863	0.863	0.863	0.863
15	0.844	0.844	0.844	0.844	0.841
16	0.872	0.872	0.872	0.872	0.879
17	0.851	0.851	0.851	0.851	0.844
18	0.831	0.831	0.831	0.831	0.844
19	0.82	0.82	0.82	0.82	0.816
20	0.807	0.807	0.807	0.807	0.811

[a]Participant: **P;** [b]Accuracy: **A;** [c]Precision: **Pr;** [d]Recall: **R;** [e]F-Measure: **F**; [f]ROC Area: **ROC**

Table 2 presents the intensive- less intensive binary classification results obtained for the 14-channel EEG. An examination of Table 2 reveals that we achieved an accuracy of 80% or higher for 15 participants. The lowest accuracy observed was 77.6% for Participant 5, while Participant 2 attained the highest accuracy of 89.8%. The average accuracy across 20 participants was 83.2%.

Table 3 illustrates related-unrelated binary classification results. As evident in Table 3, 11 participants achieved classification accuracies of 80% or higher. The lowest classification accuracy observed was 73.2%, while the highest was 88.0%. The average classification accuracy across 20 participants was 80.8%. This study additionally investigated the subject-independent classification of EEG signals using the k-NN algorithm. In subject-independent studies, training and testing procedures are conducted on EEG data collected from all participants.

Table 3. *The results of subject-dependent for related-unrelated binary task classification*

[a]P	[b]A	[c]Pr	[d]R	[e]F	[f]ROC
1	0.761	0.761	0.761	0.761	0.756
2	0.88	0.88	0.88	0.88	0.882
3	0.83	0.83	0.83	0.83	0.821
4	0.778	0.778	0.778	0.778	0.777
5	0.758	0.758	0.758	0.758	0.761
6	0.808	0.808	0.808	0.808	0.815
7	0.862	0.862	0.862	0.862	0.876
8	0.793	0.793	0.793	0.793	0.799
9	0.768	0.768	0.768	0.768	0.769
10	0.861	0.861	0.861	0.861	0.867
11	0.789	0.789	0.789	0.789	0.786
12	0.833	0.834	0.833	0.833	0.834
13	0.867	0.867	0.867	0.867	0.865
14	0.732	0.732	0.732	0.732	0.739
15	0.853	0.853	0.853	0.853	0.863
16	0.84	0.84	0.84	0.84	0.839
17	0.818	0.818	0.818	0.818	0.81
18	0.741	0.741	0.741	0.741	0.746
19	0.784	0.784	0.784	0.784	0.795
20	0.804	0.804	0.804	0.804	0.81

[a]Participant: **P;** [b]Accuracy: **A;** [c]Precision: **Pr;** [d]Recall: **R;** [e]F-Measure: **F**; [f]ROC Area: **ROC**

Table 4. *The average results of the subject-dependent analysis for intensive-less intensive and related-unrelated classification task*

	[b]A	[c]Pr	[d]R	[e]F	[f]ROC
Intensive-less intensive	0.832	0.832	0.832	0.832	0.833
Related-unrelated	0.808	0.809	0.808	0.808	0.810

[b]Accuracy: **A;** [c]Precision: **Pr;** [d]Recall: **R;** [e]F-Measure: **F**; [f]ROC Area: **ROC**

Conversely, subject-dependent studies perform these procedures on recordings obtained from a single participant. Conversely, subject-dependent studies perform these procedures on recordings obtained from a single participant.
Table 4 demonstrates the average classification performance of the k-NN algorithm on this dataset. In the intensive-less intensive classification task, the algorithm achieved average accuracy, precision, and ROC area of 83.2%, 83.2%, and 83.3%, respectively.

Table 5. *The results of the subject-independent analysis for intensive-less intensive and related-unrelated classification task*

	[b]A	[c]Pr	[d]R	[e]F	[f]ROC
Intensive-less intensive	0.792	0.792	0.792	0.792	0.792
Related-unrelated	0.775	0.776	0.775	0.775	0.775

[b]Accuracy: **A;** [c]Precision: **Pr;** [d]Recall: **R;** [e]F-Measure: **F**; [f]ROC Area: **ROC**

For the related-unrelated classification task, the average accuracy, precision, and ROC area were 80.8%, 80.9%, and 81%, respectively. Table 5 presents the subject-independent classification results for intensive-less intensive and related-unrelated tasks. In the subject-independent study, the average accuracy, precision, F-measure, and ROC area for intensive-less intensive tasks were 79.2%, while those for related-unrelated tasks were 77.5%, 77.6%, 77.5%, and 77.5%, respectively. As evident in Table 5, the performance on intensive-less intensive tasks outperformed that on related-unrelated tasks. This suggests that participants were able to differentiate between intensive-less intensive tasks more effectively using EEG signals compared to related-unrelated tasks.

The findings of the present study are further supported by the work of Arslan et al. [20]. In their investigation, they employed both subject-dependent and subject-independent approaches to classify mental mathematical tasks and silent text reading tasks using EEG data. Their results demonstrated a clear advantage of subject-dependent classification, with accuracy rates ranging from 95.8% to 99%, compared to 92.2% to 97% for subject-independent classification. This alignment of findings across studies further validates the superiority of subject-dependent EEG-based cognitive task classification.

Consistent with expectations, subject-dependent analyses yielded better accuracy, as each participant's data was used for both training and testing. Nonetheless, the subject-independent classification results remain noteworthy.

4. Conclusions

This paper proposes an approach to classifying cognitive tasks based on the analysis of EEG signals. The study investigates the application of the CWT in conjunction with machine learning algorithms for the classification of spontaneous EEG data recorded during cognitive tasks.

For classification purposes, k-NN algorithm was employed, and its performance in discriminating between cognitive tasks was evaluated. The classification results achieved by k-NN utilizing features extracted via the CWT method surpassed 79% accuracy and 77% accuracy for intensive-less intensive and related-unrelated binary task classifications in subject-independent experiment, respectively. Furthermore, the average classification results exceeded 80% for both intensive-less intensive and related-unrelated tasks, reaching 83.2% and 80.8 in the subject-dependent experiment, respectively. CWT emerges as a powerful and valuable tool for classifying EEG signals associated with complex cognitive tasks. This has promising implications for its application in EEG-based clinical diagnoses, such as epilepsy, depression, and stress. Moreover, the findings demonstrate that the k-NN algorithm can achieve high classification accuracy on diverse datasets. Refined methods and research on larger and more diverse datasets will contribute to the enhanced utility of the k-NN algorithm in real-world applications. However, this study is not without limitations. For instance, the study was conducted on a relatively small dataset. Future research will investigate the generalizability of the findings by conducting tests on larger and more diverse datasets.

Author Statements:

- **Ethical approval:** Hatay Mustafa Kemal University Hospital Research Ethics Committee (Number and No: 25.03.2021/03-2021/24)
- **Conflict of 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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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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