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Efficient Mental Arithmetic Classification Using Approximate Entropy Features and Machine Learning Classifiers

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Abstract
In the current era, detecting mental workload is one of the most important methods used to determine the mental state of humans, which in turn helps determine whether there is an issue in the brain. Machine learning became the most used field used by researchers due to its accurate ability to deal with and analyze the state of the brain. In this study, machine learning was used to classify the Mental Arithmetic Task Performance (before and after) using EEG signals. Initially, as a preprocessing method, due to the variance of the signal received from the brain, we divide the signal into Sub-bands namely alpha, beta, gamma, theta, and delta for artifact removal. Then we applied Approximate entropy (ApEn) to extract features from the signals. Next, the deduced features were applied to 8 different types of classification methods, which are ensemble classifier, k-nearest neighbor (KNN), linear discriminate (LD), support vector machine (SVM), decision trees (DT), logistic regression (LR), neural network (NN), and quadratic discriminate (QD). We have achieved an optimal result using ES, furthermore, we compared our work with other papers in the literature, and the results outperformed them.
Keywords: Electroencephalogram (EEG), Machine learning (ML), ES, SVM, KNN, LD, LR, DT, NN, QD

1. Introduction

Scientists and researchers have paid a great deal of attention to the investigation of cognition in humans from lots of fields, such as biophysics, connectomics, computational neuroscience, and signal processing. One of the primary disciplines that interest them is the study of brain patterns, activities, and emotional states and how they impact cognition. Through the past few years, lots of theoretical and empirical assistance on various problems have been considered and already been developed, including the connections across cognitive phenomena as well as the behavior of the brain's structures, the "global workspace" theory of brain function during emotions and mental activity, the dynamical properties of cortical areas and their coordination, and the interaction of brain networks during creative cognition and artistic performance (Duru and Assem 2018). To go deeply into the field, there are lots of prominent publications that have been released on mental neurophysiology, and neuroscience (Duru and Assem 2018; Duru et al. 2020).

The brain's cognitive workload can be evaluated, which is divided into objective measures and subjective ones. Subjective measuring is based on perceived feelings which are based on questionnaires. While the objective measures used physiological signals to check the cognitive workload. Whereas the common types use electroencephalogram (EEG), eye movement, electromyogram, and many other types. EEG was the tool that opened the human brain to science and scientists to discover brain mysteries especially when there is a disorder such as epilepsy, or Alzheimer's or even when a disease such as a brain tumor and COVID-19 (Al-azzawi et al. 2023; Al-Jumaili et al. 2021; Al-Jumaili et al. 2023; Al-azzawi et al. 2022; Saif). Currently, the use of modern techniques in detecting mental workload is one of the most important ways that help reveal the human mind issues, which reduces the risks of human action errors. The most important and used technology that helps in early disorder detection is the technique of extracting the brain signals by using an electroencephalogram (EEG). And then extract the most important features from these signals. In addition, there are review articles(Arico et al. 2017; Aricò et al. 2018) ,that discuss current developments and potential future directions in brain-computer interface techniques and methods utilized to gauge and classify emotional disorders scientifically. The basic methods of spectral (Soleymani, Pantic, and Pun 2011; Kortelainen, Väyrynen, and Seppänen 2015), and coherence analysis (Weiss and Mueller 2003; González-Garrido et al. 2018), are among the most well-known and potent instruments utilized to disclose the significant aspects of neurological operation and to study the activation of functional and anatomical brain regions during mental tasks. It is necessary initially to classify the brain's function during cognitive engagement utilizing these novel markers before turning this study in the direction of investigating the new opportunities of nonlinear methods for signal processing. Table 1 below summarizes methods that have been used in various studies in order to classify the mental workload.

Table 1. Various studies classified the mental workload.

Ref	Task	Feature domain	Feature types	Data divided types	Classifier types	Acc%
(Zarjam, Epps, and Chen 2011)	Silent Reading	1,3,5	T-TEST	HOLD-OUT	SVM	83
(Zarjam et al. 2013)	Complex Task And Memory	2	NA	10-FOLD	SVM	82
(Yu et al. 2015)	Visual Degradation	2,4	NA	4-FOLD	SVM	80
(So et al. 2017)	Cognitive And Motor	2	NA	10-FOLD	SVM	75
(Mazher et al. 2017)	Multimedia Learning	5,6	DWT	NA	SVM	88
(Bashivan, Yeasin, and Bidelman 2015)	Sternberg	2,5	RF	10-FOLD	SVM	92
(Dimitrakopoulos et al. 2017)	N-Back	6	SFS	LOSOCV	SVM	87
(Wang, Gwizdka, and Chaovalitwongse 2015)	N-Back	1,2,3	MRMR	10-FOLD	SVM	84
(Yin and Zhang 2014)	ACAMS	2	RFE	HOLD-OUT	SVM	74
(Zhang, Yin, and Wang 2014)	ACAMS	2	AES, LPP	10-FOLD	SVM	93
(Ke et al. 2014)	N-Back	2	RFE	3-FOLD	SVM	NA
(Baldwin and Penaranda 2012)	Memory Task	2	TOTAL POWER	HOLD-OUT	ANN	85

(Penaranda and Baldwin 2012)	N-Back	2	POWER	NA	ANN	81
(Wilson and Russell 2003a)	ATM	2	SFR	HOLD-OUT	ANN	88
(Tremmel et al. 2019)	N-Back	2	FFT	4-FOLD	LDA	63
(Roy et al. 2016)	Sternberg	1,2	NA	10-FOLD	LDA	91
(Kakkos et al. 2019)	Flight	6	RFE	10-FOLD	LDA	82
(Kohlmorgen et al. 2007)	Real Drive	2	NA	11-FOLD	LDA	92
(Aricò et al. 2016)	ATM	2	NA	HOLD-OUT	SWLAD	NA
(Borghini et al. 2017)	ATM	2	FFT	HOLD-OUT	SWLAD	NA
(Chakladar et al. 2021)	N-Back	4	MI	10-FOLD	NB	84
(Dimitriadis et al. 2015)	Arithmetic	6	LPP	HOLD-OUT	KNN	75
(Wang et al. 2012)	MATB	3	FT	5-FOLD	HB	80
(Tao et al. 2019)	ACAMS	1,2,5	NA	HOLD-OUT	ELM	93
(Cheema et al. 2018)	N-Back	1,2,3	MRMR	HOLD-OUT	KNN, DT, RF, SVM	84
(Appriou, Cichocki, and Lotte 2018)	N-Back	4	MI	HOLD-OUT	CSP+LDA	72
(Friedman et al. 2019)	Raven Test	2,5,6	NA	HOLD-OUT	ANN, LR, XGB	71

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Based on the results obtained in previous studies, they were acceptable to some extent. We are trying to increase the accuracy by proposing a new classification method by using machine learning. The advantages of the study can be summarized in the following points:1) High ability to classify mental workload using 1-second brain signals. 2) Use a Band Pass filter to reduce unwanted signals. 3) Providing a method that has the potential to be applied in the health sector and that would help doctors in classifying mental workload.

2. METHODOLOGY

In this study, publicly available data from the Internet were employed. The datasets contained two types of brain signals: (before and after) the mental strain. Where (24 subjects) performed a hard math calculation (average number of operations per 4 minutes = 21, SD = 7.4) and (12 subjects) performed a easy math calculation (average number of operations per 4 minutes = 7, SD = 3.6). The brain signals were collected using 23 channels using the 10-20 system. Table 2 shows the details of the data that were used in this study, Females are marked with "♀", males are marked with "♂", as well as for the two groups "1" for the hard calculation and "0" for the easy calculation. Figure 1 which shows the details of the signal before and after the mental workload (Zyma et al. 2019).

Table 2. Subjects details used in this study

Participate	Age	Gender	Number of subtractions	Rank quality
subject00	21	♀	9.7	0
subject01	18	♀	29.35	1
subject02	19	♀	12.88	1
subject03	17	♀	31	1
subject04	17	♀	8.6	0
subject05	16	♀	20.71	1
subject06	18	♂	4.35	0
subject07	18	♀	13.38	1
subject08	26	♂	18.24	1
subject09	16	♀	7	0
subject10	17	♀	1	0
subject11	18	♀	26	1
subject12	17	♀	26.36	1
subject13	24	♂	34	1
subject14	17	♀	9	0
subject15	17	♀	22.18	1
subject16	17	♀	11.59	1
subject17	17	♀	28.7	1
subject18	17	♀	20	1
subject19	22	♂	7.06	0
subject20	17	♀	15.41	1
subject21	20	♀	1	0
subject22	19	♀	4.47	0
subject23	16	♀	27.47	1
subject24	17	♂	14.76	1

subject25	17	♂	30.53	1
subject26	17	♀	13.59	1
subject27	19	♀	34.59	1
subject28	19	♀	27	1
subject29	19	♂	16.59	1
subject30	17	♂	10	0
subject31	19	♀	19.88	1
subject32	20	♀	13	1
subject33	17	♂	21.47	1
subject34	18	♀	31	1
subject35	17	♀	12.18	1

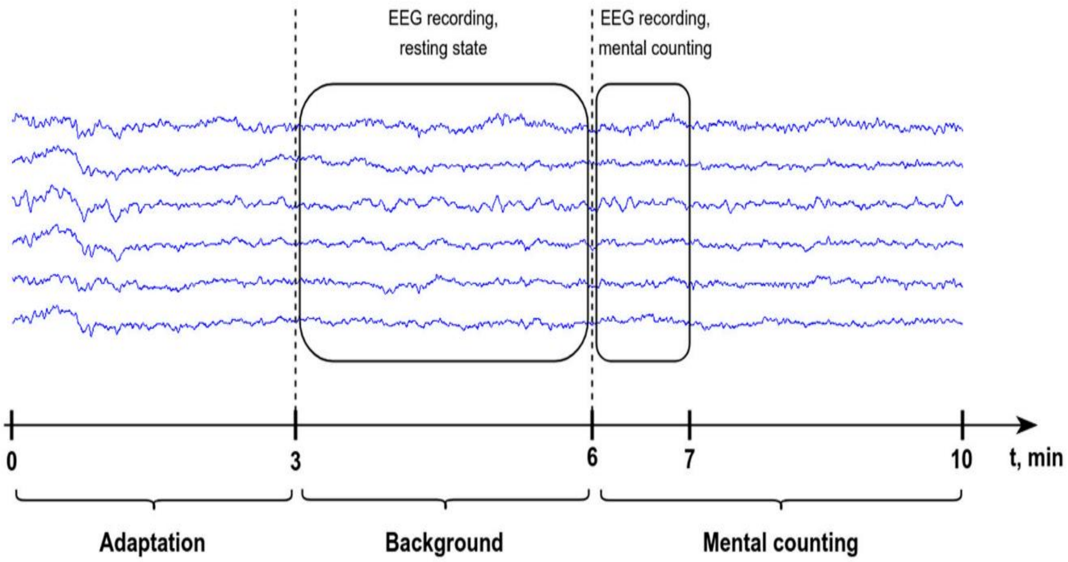

Figure 1. The Data Signal Before and After the Mental Workload

2.1. Feature Extraction

In this section, we explain the data extraction method, where the five sub bands are inserted into the Long Entropy in order to extract the features from these signals. To obtain the features via the EEG data in our research, we employed Long Entropy which is described as a method of determining if a time series of data is regular or random. Because Long Entropy lower sensitivity to noise, it is employed for short-length signals. The total length of the data slice that is being compared, e, and N are all indicated in Eq. 1 where r stands for the similarity criteria.

$$ApEn(E,r,N) = \frac{1}{(N-e+1)}\sum_{i-1}^{N-e+1} log \quad C_i^e\,(r) - \frac{1}{N-e}\sum_{i=1}^{N-e} log\, C_i^{e+1}\,(r) \qquad (1)$$

2.2. Classification

There are several classification strategies in machine learning, each with its own way of categorization. In this research, 8 different types of classification methods were used, which are ensemble classifier, k-nearest neighbor (KNN), linear discriminate (LD), support vector machine (SVM), decision trees (DT), logistic regression (LR), neural network (NN), and quadratic discriminate (QD). K-nearest neighbor (KNN), which stands for how to choose the optimal value of K. It belongs to the algorithms that under the supervised type used to solve classification and regression problems. KNN can naturally handle multi-class cases and it's one of the oldest, simplest, and most accurate algorithms. Meanwhile, linear discriminant analysis (LDA) applies to two separate but related techniques. The first step is to create a classifier. Each class is modeled as Gaussian (with a covariance matrix and a mean vector) given a set of variables as the data representation. Observations are now assigned to the nearest mean vector class based on Mahalanobis distance. If two classes share a covariance matrix, the decision surfaces between them become linear. Support Vector Machine (SVM) is one of the algorithms that deal with huge datasets and also deals with multidomain data since it is a supervised learning algorithm. SVM on the other hand, is theoretically difficult and computationally costly. Decision trees (DT) are suitable for many statistics and machine learning applications at multiple levels of measurement and with varied data quality. Trees are resilient in the presence of missing data and provide several methods for integrating missing data into the final models. Although trees are strong, they are also adaptable and simple to utilize. This ensures the generation of high-quality outcomes with minimum assumptions. Logistic regression (LR) was well-known for its performance as a machine learning (ML) model for predicting the risk of major illnesses with low incidence and simple clinical factors. Among the top models were logistic regression, gradient boosting machine, and neural network. MATLAB neural network (NN) tool is the preferred cascade forward-back algorithm for the classification of EEG signals. NN offers structure development adjustments based on needs as well as tools for analyzing the outcomes, making it an excellent choice for tackling a difficult problem in a straightforward manner. The backpropagation algorithm has a simple structure, several parameters that may be adjusted, a large training algorithm, and strong operating performance. Finally, Quadratic discriminant classifier which is a common classification method that uses quadratic discriminant analysis to locate or distinguish variables (Alkan and Günay 2012; Srivastava, Gupta, and Frigyik 2007).

2.3. Performance Evaluation

In order to assess the efficacy of the suggested approach, many measures have been taken. These measurements include receiver operating characteristic (ROC) analysis, accuracy, sensitivity, specificity, precision, negative predictive value (NPV), F1-Score, and Matthew's correlation coefficient (MCC) values. The formulae utilized to determine the levels for every metric are displayed in Table 3.

Table 3. Performance evaluation that have been considered in this study.

Function name	Equations
Accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$
Sensitivity	$\frac{TP}{TP+FN}$
$Specificity$	$\frac{TN}{TN+FN}$
$Precision(PPV)$	$\frac{TP}{TP+Fp}$
Negative Predictive Value (NPV)	$\frac{TN}{TN+FN}$
$F1-score$	$\frac{2*TP}{2*TP+FP+FN}$
MCC	$\frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

3. RESULTS AND DISCUSSION

Table 4 shows the results of the confusion matrices that were obtained by using classifiers, as the results were uneven in terms of the accuracy of classification.

Table 4. The confusion matrices obtained by using classifiers.

Feature Name	Classes Name		SVM		KNN	
			Predicted Class		Predicted Class	
Long Entropy	Actual Class	Before	6411	33	6425	19
		After	62	2169	32	2199
	Classes Name		LD		LR	
			Predicted Class		Predicted Class	
	Actual Class	Before	6294	150	6189	255
		After	600	1631	430	1801
	Classes Name		QD		NN	
			Predicted Class		Predicted Class	
	Actual Class	Before	6375	69	6389	55
		After	62	2169	74	2157
	Classes Name		DT		ES	

		Predicted Class		Predicted Class	
Actual Class	Before	6094	350	6440	4
	After	437	1794	16	2215

In this section we will discuss the results obtained by using 8 different types of classifiers. Whereas, the highest results were obtained by using extracted brain signals (before and after) mental workload, which were used as inputs to the workbooks. In terms of the results shown in Table 5, the best classifier that obtained results was ES, as the results achieved were all 99. While the lowest results were obtained by the DT classifier, the accuracy obtained was 90, which is the lowest result among all classifiers. As the rest of the workbooks had different results, but mostly the results were acceptable to some extent.

Table 5. The accuracy obtained from the 8 classifiers.

Classifier types	Feature extraction	Evaluation metrics						
		Acc	Sen	Spec	Pre	Npv	F1-score	Mcc
SVM	long entropy	98	99	98	99	97	99	97
KNN		99	99	99	99	98	99	98
LD		91	91	91	97	73	94	76
LR		92	93	87	96	80	94	78
QD		98	99	96	98	97	98	96
NN		98	98	97	99	96	99	96
DT		90	93	83	94	80	93	75
ES		99	99	99	99	99	99	99

In the next section, Table 6 compares our work and results with papers that used different techniques with different mental tasks to be sure about the results that we obtained from different classifiers. Our proposed method shows that we achieved higher accuracy compared to the papers, and the results were perfect for all evaluation metrics using features that were extracted using Long_Entropy with an ES classifier. Moreover, for the other classifiers, all of them obtained results over 90%, which is fairly acceptable if compared to the other methods proposed in the state-of-the-art.

Table 6. Comparing various papers techniques with their results.

Ref	Task	Feature Domain	Feature Types	Data Divided Types	Classifier Types	Acc%
(Wilson and Russell 2003b)	MATB	2	SFR	Hold-Out	ANN	86
(Almogbel, Dang, and Kameyama 2019)	Memory and Delay	5	Feature Fusion	LOSOCV	SVM	NA
(Zarjam, Epps, and Lovell 2015)	Arithmetic	3	KW_Test	LOSOCV	ANN	98
(Dehais et al. 2019)	Flying	1,3	MRMR	5-Fold	LDA	70
Ours	**Arithmetic**	**1**	**Long_Entropy**	**5-Fold**	**ES**	**99**

4. Conclusion

The mental workload is one of the most important studies that are based on taking brain signals because it has a great effect on treating people, especially if the brain condition is detected in the early times. In this study, we classified brain signals that depend on mental workload in two cases (before and after). Long_Entropy was used in order to extract features from the signals, where we used these features as inputs to 8 types of classifiers. The best results were obtained by using the ES classifier compared to other classifiers used. We concluded that this proposed method has the ability to deal with this type of data and can obtain high accuracy. Moreover, for future work, we can apply this technique to other diseases and increase the number of datasets. Furthermore, we plan to convert the EEG signal to an image and apply it to the novel convolutional neural network.

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CONFLICT OF INTEREST

The author has no conflict of interest.

AUTHOR STATEMENT

S.A. conceived of the presented idea and developed the method and performed the computations.

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