Exploring Differential Entropy and Multifractal Cumulants for EEG-based Mental Workload Recognition

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***Abstract*—In the current research, two nonlinear features were utilized for the design of EEG-based mental workload recognition: one feature based on differential entropy and the other feature based on multifractal cumulants. Clean EEGs recorded from 36 healthy volunteers in both resting and task states were subjected to feature extraction via differential entropy and multifractal cumulants. Then, these nonlinear features were utilized as input for a fuzzy KNN classifier. Experimental results showed that the multifractal cumulants feature vector achieved an AUC of 0.951, which is larger than the differential entropy feature vector (AUC = 0.935). However, the combination of both feature sets resulted in added value in identifying these two mental workloads (AUC = 0.993). Furthermore, the multifractal cumulants feature vector (best classification accuracy = 94.76%) obtained better classification results than the differential entropy feature vector (best classification accuracy = 92.61%). However, the combination of these two feature vectors achieved the best classification results: accuracy of 96.52%, sensitivity of 97.68%, specificity of 95.58%, and F1-score of 96.61%. This shows that these two feature vectors are complementary in identifying different mental workloads.**

***Keywords*—Mental workload; EEG; nonlinear analysis; multifractal; differential entropy; fuzzy KNN; classification**

I. Introduction

Lately, there has been tremendous progress in the development and use of detection tools and artificial intelligence. As a result, they are now widely used to monitor human mental states in different areas [1]. These technologies are practically applied in passive brain-computer interfaces and human-robot interaction [2]. In this context, assessing cognitive workload has become highly important and has attracted a lot of attention. It measures the mental effort required considering the available cognitive resources. Monitoring and evaluating various factors like emotions, fatigue, and stress that affect cognitive workload have become crucial due to their potential impact on people's well-being and performance in real-world situations [3], [4]. Therefore, recognizing and understanding cognitive workload is extremely significant for improving human productivity, safety, and overall quality of life.

Until now, cognitive workload measurements have been classified into two types: objective and subjective measures. Subjective measures rely on self-assessment and perceptions of the operators, often utilizing questionnaires like the Subjective Workload Assessment method to evaluate cognitive workload. While these approaches are easy to implement, they lack objectivity, real-time feedback, and precise results [5]. On the other hand, objective measures primarily rely on task performance recordings and various biological signals, which minimize interference with the task and address the aforementioned limitations [6]. Commonly used physiological signals include heart rate, respiration, electroencephalogram (EEG), eye tracking, and electromyogram [7]. Among these, EEG is a popular choice due to its convenience, excellent temporal resolution, availability, security, and affordability [8], [9]. Hence, this study focuses on the recognition of cognitive workload using EEG-based methods.

EEG signals possess distinct characteristics, including noise, weakness, nonlinearity, and non-stationarity, which vary among individuals [10]. Consequently, it is a significant challenge to identify robust patterns in EEG signals specific to a particular state. Traditional analytical approaches rely on statistical testing to detect differences in features like power variations within standard EEG frequency bands [11]. However, these methods may lack adequate modeling capacity or fail to uncover causal relationships [12]. To overcome these challenges, numerous studies have proposed various machine-learning techniques [13]. Machine learning can effectively learn unique features that capture inherent patterns in the data and construct predictive models [14]. For instance, a proposed method integrates ECG, EEG, and electrooculography (EOG), demonstrating superior predictive capability compared to individual analyses [15]. Similarly, another research showcases high accuracy by combining ECG, EEG, and respiration rate for the classification of mental conditions [16]. Furthermore, combining EEG and ECG yields even better outcomes compared to using EEG signals alone [17]. However, utilizing multiple sensors and processing multiple physiological signals can pose computational and processing challenges. As a result, many researchers have concentrated on using EEG alone to identify mental workload. Several studies have utilized spectral, statistical, and fractal analysis along with various classifiers to detect different mental states from EEG signals. For instance, Zarjam et al. presented a mental workload recognition system that incorporates time, time-frequency, and nonlinear features of EEGs from five healthy volunteers, a statistical feature selection method based on t-test, and SVM classifier. They achieved an accuracy of 83% using the hold-out cross-validation technique in recognizing three different levels of cognitive workload [18]. Walter et al. computed the spectral features of EEGs from 21 healthy subjects as input to an SVM classifier and reported an accuracy of 82% using the 10-fold cross-validation technique in detecting three levels of mental workload [19]. Tremmel et al. also computed the spectral features of EEGs from 15 healthy subjects as input to a regularized LDA classifier and reported an accuracy of 63% using the 4-fold cross-validation technique in detecting three levels of mental workload [20]. Kakkos et al. calculated the functional connectivity of EEG signals from 33 healthy subjects as input to an ensemble LDA classification model and reported an accuracy of 82% using the 10-fold cross-validation technique in detecting three levels of mental workload [21]. Wang et al. calculated the time-frequency features of EEG signals from eight healthy subjects as input to a hierarchical Bayes classifier and reported an accuracy of 80% using the 5-fold cross-validation technique in detecting three different levels of cognitive workload [22]. Gevins et al. computed the spectral features of EEGs from eight healthy subjects as input to a neural network classifier and reported an accuracy of 80% using the hold-out cross-validation technique in detecting three different levels of cognitive workload [23].

Although the EEG signal exhibits nonlinear and chaotic characteristics, and nonlinear analysis techniques in signal processing have made significant advancements, there is a scarcity of studies exploring the potential of various nonlinear analysis methods in identifying cognitive workload. The existing studies that have employed nonlinear techniques have reported unsatisfactory outcomes. As a result, this study strives to enhance previous endeavors by employing two unique nonlinear analyses and machine learning techniques for the classification of resting and task-related EEG data. The two unique nonlinear analyses are performed according to differential entropy and multifractal cumulants. Therefore, the contribution of this study is twofold. First, multifractal cumulants and differential entropy are examined for the first time to recognize mental workload. Multifractal analysis of brain signals can provide insights into the complex and non-linear dynamics of neural activity. While the direct relationship between multifractal cumulants of brain signals and mental workload is still an area of ongoing research, there are potential connections and implications. Multifractal analysis could potentially be used to distinguish between different mental states, such as periods of high versus low mental workload. Patterns in multifractal cumulants might reveal underlying neural dynamics linked to cognitive processing and workload variations. On the other hand, higher mental workload often requires increased cognitive processing and information integration. The differential entropy of brain signals could reflect the complexity and amount of information being processed by the brain during tasks associated with different levels of mental workload. However, none of the previous studies have examined these two important features for identifying mental workload. Second, a fuzzy classifier (fuzzy KNN) was applied to the extracted features. Fuzzy classification of brain signals can play a role in decoding the neural correlates of mental workload and providing valuable insights into cognitive states and processes. By exploiting the flexibility and adaptive nature of fuzzy logic, it is possible to capture the complexity of brain dynamics associated with different levels of mental workload.

II. Methods

In this section, a comprehensive plan outlining the methods and techniques used to accomplish the research objectives is provided. It encompasses a thorough explanation of the experimental design, dataset, and analysis procedures employed in this study. Each step is presented in a systematic manner, with a focus on the crucial variables, instruments, and statistical methods utilized.

A. EEG Dataset

In this research, an openly accessible EEG database [24] was employed to investigate mental cognitive workload. The study enrolled 36 healthy volunteers (75% female) within the age range of 18 to 26 years. Participants met the criteria of having normal color vision, and visual acuity, and no history of cognitive or mental disorders or learning disabilities. To induce cognitive activity, participants were instructed to complete arithmetic tasks involving consecutive number subtraction while their EEG data was captured. The EEG signals were recorded using Ag/AgCl electrodes positioned on the scalp following the 10-20 standard system. Sixteen scalp locations were selected, including Fp1, T5, Fp2, F8, F3, T3, F4, Fz, F7, C3, O1, C4, O2, Cz, T4, and T6. A reference was established by connecting the channels to A1 and A2, positioned on the earlobes. Electrode impedance was maintained below 5 kOhm, and the sampling rate was set at 500 Hz. To reduce noise and artifacts, a low-pass filter with a cutoff frequency of 45 Hz, a high-pass filter with a cutoff frequency of 0.5 Hz, and a notch filter with a center frequency of 50 Hz were used to filter the recorded EEGs. Before EEG recording, participants were instructed to relax during a resting-state period and mentally count during the arithmetic tasks without verbalizing. The recording process consisted of a three-minute adaptation phase, followed by three minutes of resting state with closed eyes, and concluding with four minutes of performing the arithmetic task. The timeline of the recording process is visualized in Fig. 1.

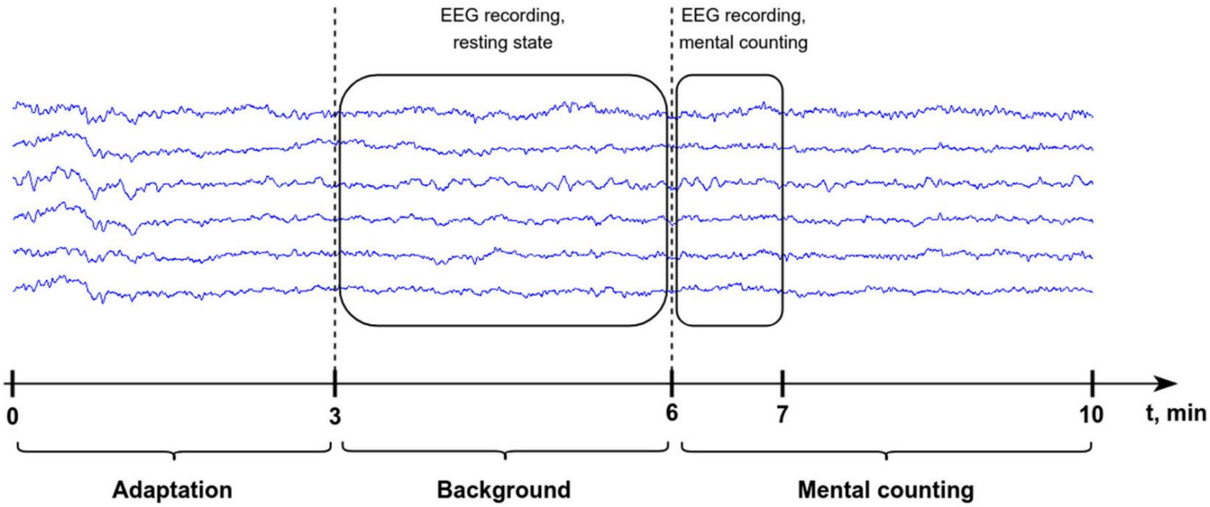

Fig. 1. The time course of the EEG recording procedure [24].

B. Proposed Framework

The general framework for EEG-based mental workload recognition is shown in Fig. 2. First, Clean EEGs were subjected to feature extraction via differential entropy and multifractal cumulants. Then, these nonlinear features were utilized as input for a fuzzy KNN classifier.

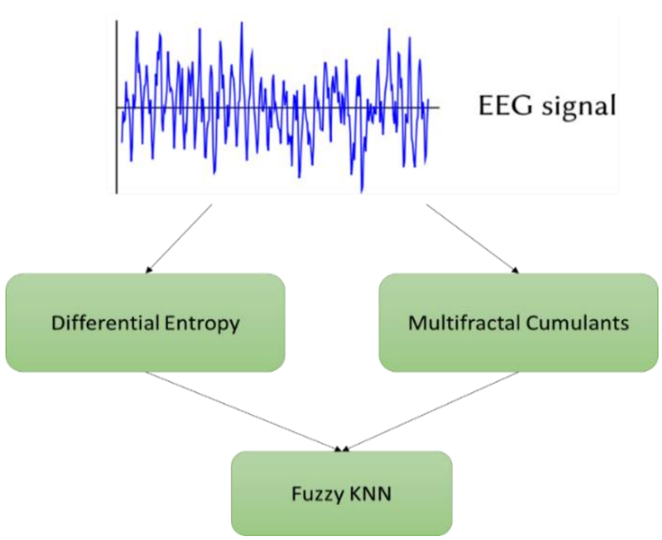

Fig. 2. General framework for EEG-based mental workload recognition.

C. Differential Entropy

Differential entropy is a concept widely used in information theory and statistics to measure the uncertainty or randomness present in a continuous random variable. The underlying assumption is that engaging in a cognitive task has the potential to either heighten or diminish the predictability of the EEG signal. This altered predictability, when quantified by this feature, can be recognized via classifiers. For instance, motor activity produces discernible rhythmic patterns that contrast with the resting state of neurons. Regardless of the specific frequencies associated with both motor activity and the resting state, the presence of any type of activity will induce a variation in the predictability of the EEG signal. Mathematically, differential entropy is defined by [25]:

$$DE = -\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx = \frac{1}{2}\log(2\pi e\sigma^2) \quad (1)$$

where, the signal X has a Gaussian distribution N (μ, σ2). In the feature extraction step, differential entropy was calculated in each EEG frequency band: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-40 Hz).

D. Multifractal Cumulants

Multifractal cumulants can be viewed as a statistical measure of the relationships between different frequency bands. The multifractal approach provides insights into how these bands are interconnected at any given moment. The underlying hypothesis suggests that specific mental activities not only affect the power of various EEG frequency bands but also impact the distribution of this power among the bands. Essentially, the multifractal cumulants of the signal capture a distinctive pattern of inter-band relationships, which differs from the commonly used approach of analyzing power within individual frequency bands. Previous research has demonstrated the potential of utilizing the multifractal spectrum for EEG classification [26]. Our chosen method for extracting the multifractal spectrum involves performing a discrete wavelet transform on the signal and extracting the wavelet leader coefficients [27]. Then, following the methodology outlined in study [28], the cumulants of the leaders as classification features were employed. Let x(t) denote the signal under analysis. According to the perspective presented in [29] on multifractal analysis, the statistical properties of x(t) are related to those of a scaled version of the signal, x(at). This scaling in time corresponds to a frequency shift in the context of frequency analysis. Therefore, an alternative interpretation of the multifractal cumulants feature is that it characterizes some form of inter-frequency information, as explained in the introduction of this section.

- The process of implementing the multifractal cumulants extraction algorithm is as follows:
- The discrete wavelet transform is utilized to decompose the time series x(t) and obtain the wavelet coefficients $w(s,t_s)$ at every time interval t_s and dyadic scale s.
- The wavelet leaders are calculated at every scale s by extracting the maximum coefficients among all samples obtained by calculating $w(s,t_s)$, $w(s,t_{s-1})$, and $w(s,t_{s+1})$.
- The partition functions are calculated for a sufficient range of exponents q as follows:

$$F(s,q)=\frac{1}{N_s}\sum_{t_s=1}^{N_s}|w(s,t_s|^q \tag{2}$$

- To obtain the multifractal spectrum, either a Legendre transform or a direct estimation of the Holder exponent density was employed, as described in[30]. However, in the current approach, a more recent technique introduced by study [28] was adopted. This technique involves computing the wavelet leader cumulants of orders 1-5, which are further detailed in the referenced paper. According to study [28], the initial cumulants already encompass a significant amount of practical information for characterizing the distribution of Holder exponents. In the context of a classification task, this condensed form of information can be effectively utilized.
- The first five cumulants were calculated for the leaders at every scale, denoted by s. In a signal with a size between 2L and 2L+1, where L represents the maximum levels of the wavelet transform, a cumulative count of 5 multiplied by L cumulants was obtained for the signal. These cumulants gradually encompass an increasing number of frequency bands as the scale rises. Ultimately, the feature vector consists of these 5 multiplied by L cumulants per channel.

E. *Fuzzy K-nearest neighbor (FKNN)*

The fuzzy k-nearest neighbor (FKNN) classifier emerged as one of the leading advancements in the field of KNN algorithms. It operates by incorporating membership degrees for classifying data that contains uncertainties. In FKNN, each new query sample is assigned membership degrees to different classes, with the highest degree playing a decisive role in classification [31]. The assigned membership degree reflects the proportion to which the query sample belongs to each available class. These degrees are then weighted based on the inverse distance between the query sample and its k nearest neighbors within the membership function. Additionally, a fuzzy strength parameter known as 'm' is introduced to determine the relative importance of distance when evaluating the contribution of neighbors to the membership degree. The membership degree for the query sample y in each class i, as determined by the k nearest neighbors, is measured according to the following approach:

$$u_i(y)=\frac{\sum_{j=1}^{k}u_{ij}\left(\frac{1}{\|y-x_j\|^{\frac{2}{m-1}}}\right)}{\sum_{j=1}^{k}\left(\frac{1}{\|y-x_j\|^{\frac{2}{m-1}}}\right)} \tag{3}$$

where, u_{ij} denotes the membership of the sample jth in the class ith of the training subset and m = 2.

III. Results

After the preprocessing of EEG data, various features were computed from all channels. The comparison of raw EEG signals between the rest and task conditions is presented in Fig. 3. It can be observed that there were no noticeable distinctions between the two cognitive workload states. Moreover, Fig. 4 shows the differential entropy values for each EEG frequency band at rest and task states in the F3 channel. As can be seen, the entropy values in all frequency bands are higher in the task state than in the rest state. In other words, the complexity of the EEG signal in different frequency bands is higher in the task state than in the rest state.

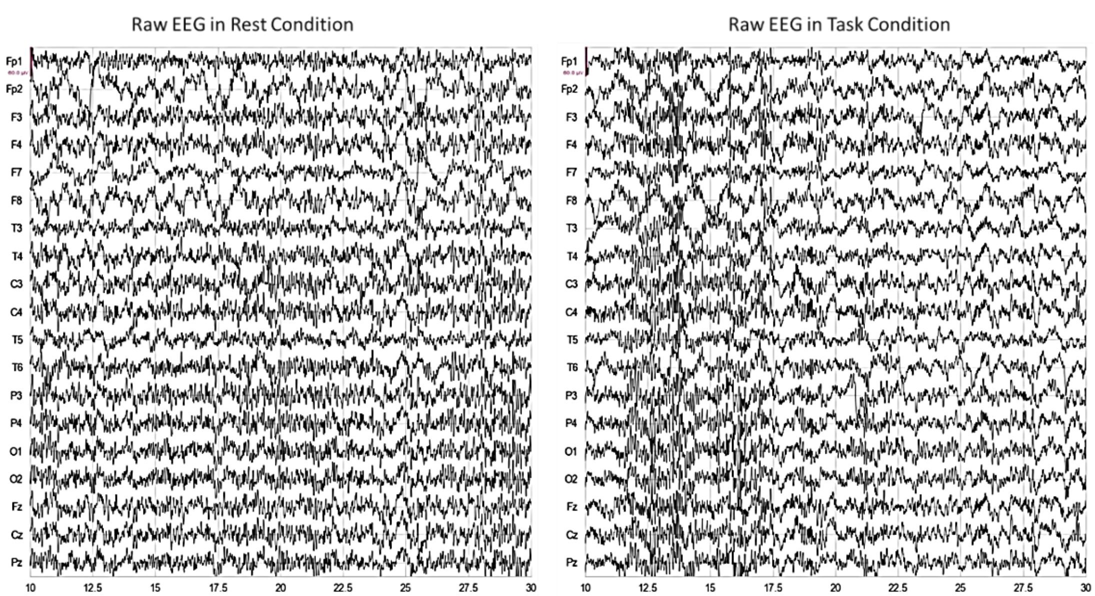

Fig. 3. A sample of EEGs for rest (left) and task (right) conditions.

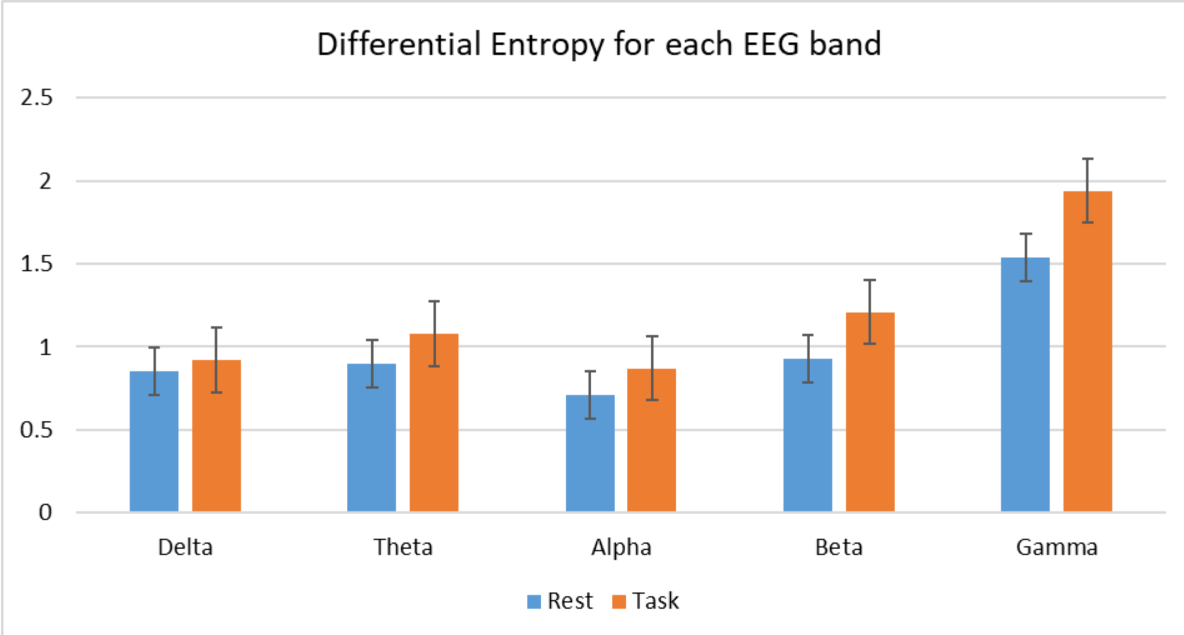

Fig. 4. Differential entropy for each EEG frequency band at rest and task states in the F3 channel.

To determine the recognition value of each of the feature vectors (i.e., differential entropy feature vector, multifractal cumulants feature vector, and combined feature vector), ROC curves corresponding to each feature category were obtained. Fig. 5 shows the ROC curves obtained for each feature category. As shown, the multifractal cumulants feature vector achieved an AUC of 0.951, which is larger than the differential entropy feature vector (AUC = 0.935). However, the combination of both feature sets resulted in added value in identifying these two mental workloads (AUC = 0.993).

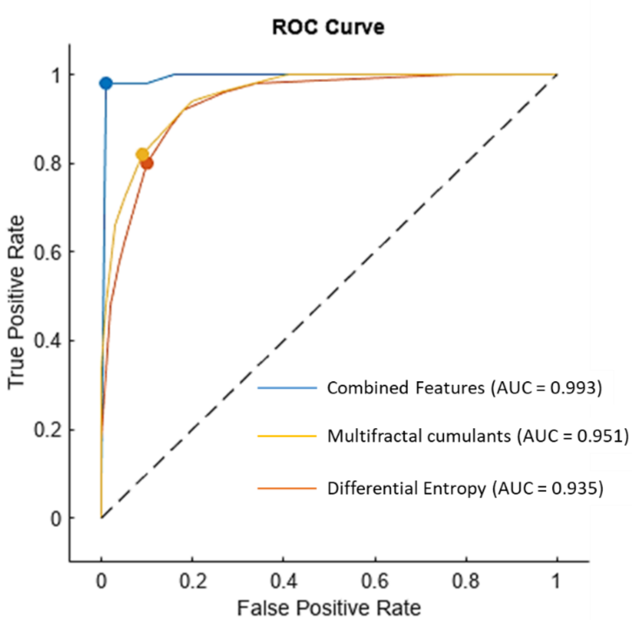

Fig. 5. ROC curves were obtained for each feature category.

In the next step, each feature vector was used as input for the classifier. In addition, to more accurately evaluate the performance of the proposed classifier (FKNN), several classical classifiers were used for comparison: KNN, linear SVM, LDA, Naïve Bayes, decision tree, and random forest. In this binary classification problem, there are two distinct classes: task or positive (P) and rest or negative (N). The classification models yield four potential outcomes: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The predicted class determines T and F, while the actual class determines P and N. Accuracy, sensitivity, specificity, and F1-score were the performance measures used to evaluate the classification. In every chosen feature vector, the data was divided into three parts: a training set of 60%, a validation set of 20%, and a testing set of 20%. To maintain the same class proportions throughout the divided sets, a stratified random sampling technique was employed during the sampling process. For cross-validation, the holdout method was utilized, generating six random splits of the training and validation sets. Tables I to III show the classification results of rest and task EEGs by differential entropy, multifractal cumulants, and combined feature vectors using different classifiers, respectively. As shown in Table I, the FKNN classifier using the differential entropy feature yielded an accuracy of 92.61%, sensitivity of 90.42%, and specificity of 94.55% and F1-score of 92.43% for mental workload recognition. After FKNN, SVM and LDA performed best among other classifiers with 91.16% and 90.89% accuracy, respectively. Multifractal cumulants achieved better results than differential entropy, as shown in Table II. Again, the FKNN classifier outperformed the other classification models with an accuracy of 94.76%, a sensitivity of 95.41%, a specificity of 94.15%, and an F1 score of 94.77%. According to the ROC curve analysis results, as expected, the multifractal cumulants feature vector (best classification accuracy = 94.76%) obtained better classification results than the differential entropy feature vector (best classification accuracy = 92.61%). However, the combination of these two feature vectors achieved the best classification results: accuracy of 96.52%, sensitivity of 97.68%, specificity of 95.58%, and F1-score of 96.61%. As shown, in Table III, this excellent result was achieved by the FKNN classifier. This shows that these two feature vectors are complementary in identifying different mental workloads. In addition, FKNN, SVM and LDA classifiers produced overall better results than other classifiers.

TABLE I. CLASSIFICATION RESULTS OF RESTING AND TASK EEGS THROUGH DIFFERENTIAL ENTROPY FEATURE VECTOR AND FKNN COMPARED TO OTHER CLASSIFIERS

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
FKNN	**92.61**	**90.42**	**94.55**	**92.43**
KNN	88.47	87.29	89.73	88.49
SVM	91.16	90.25	92.01	91.12
LDA	90.89	89.66	92.05	90.83
Naïve Bayes	83.49	82.12	84.81	83.44
Decision Tree	84.92	84.16	85.69	84.91
Random Forest	84.50	83.10	85.97	84.51

TABLE II. CLASSIFICATION RESULTS OF RESTING AND TASK EEGS THROUGH MULTIFRACTAL CUMULANTS FEATURE VECTOR AND FKNN COMPARED TO OTHER CLASSIFIERS

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
FKNN	**94.76**	**95.41**	**94.15**	**94.77**
KNN	89.11	88.36	90.00	89.17
SVM	92.39	92.98	91.74	92.35
LDA	93.21	94.36	92.10	93.21
Naïve Bayes	84.91	84.14	85.72	84.92
Decision Tree	86.32	86.93	85.65	86.28
Random Forest	85.97	85.09	86.90	85.98

TABLE III. CLASSIFICATION RESULTS OF RESTING AND TASK EEGS THROUGH COMBINED FEATURE VECTORS AND FKNN COMPARED TO OTHER CLASSIFIERS

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score (%)
FKNN	**96.52**	**97.68**	**95.58**	**96.61**
KNN	91.79	92.35	91.22	91.78
SVM	93.62	94.47	93.07	93.76
LDA	94.05	95.51	92.87	94.17
Naïve Bayes	86.13	86.90	85.35	86.11
Decision Tree	88.82	87.69	90.03	88.84
Random Forest	89.40	90.24	88.62	89.42

IV. DISCUSSION

An automated EEG-based system based on two new nonlinear features and a fuzzy classifier (FKNN) was suggested in this research for mental workload recognition. A good accuracy of 96.52% was obtained through the combination of the feature vectors extracted by two nonlinear analyses and the FKNN classifier. Mental workload serves as an important measure for assessing the cognitive demands placed on individuals during specific tasks. Its significance extends to various fields such as healthcare and education. It has been observed that nonlinear features extracted from EEG signals offer promising potential for detecting mental workload. EEG, a technique that records brain activity, captures the brain's electrical signals, which are intricate and nonlinear in nature [32]. Analyzing these signals using conventional linear methods proves challenging [33]. Nonlinear analysis of EEG signals, accomplished through mathematical techniques, enables the capture of the brain's dynamic and complex activities [34], [35], [36]. By extracting nonlinear features from EEG signals, valuable insights can be gained into the brain's functional connectivity, complexity, and synchronization, which are not easily identifiable using linear techniques [37]. The benefits of nonlinear analysis of EEG signals are numerous, including the ability to detect subtle changes in brain activity [38], identify abnormal brain activity associated with neurological disorders [39], [40], [41], [42] and develop more accurate diagnostic tools for brain disorders [33]. In essence, the nonlinear nature of EEG signals presents researchers and clinicians with a unique opportunity to delve into the intricate dynamics of the brain and devise more effective strategies for identifying mental workload.

In contrast, the outcomes achieved through the proposed method in this research exhibit great promise when compared to previous investigations. Table IV displays a comparative analysis of the proposed approach and other machine learning-based methods applied to EEG analysis for mental workload recognition. When considering the same unipolar EEG signals, the method presented in this study demonstrates satisfactory results compared to previous approaches. This study introduces a novel machine learning model that employs EEG nonlinear features to detect mental workload. Notably, unlike many prior studies that relied on small EEG datasets for evaluation, the current method was examined using a relatively larger dataset, yielding acceptable outcomes. The findings of this research hold potential implications for understanding the neural mechanisms underlying different levels of mental workload, particularly in clinical fields such as psychology and psychiatry. Nevertheless, it is essential to recognize the limitations of this study, as well as similar studies. One notable drawback is the limited clinical implications and generalizability of the findings. Further evidence is required to establish the effectiveness of employing EEG-based machine learning techniques in mental workload detection, including their performance in individuals with diverse physical or mental conditions. Moreover, a broader range of EEG datasets specific to various levels of cognitive workload is crucial to effectively utilize these approaches, given the intensive data requirements of machine learning techniques for optimal results. Nonetheless, the proposed method can potentially serve as a computer-aided detection (CAD) tool for clinical applications. Additionally, the presented framework offers advantages such as reduced labor, time efficiency, and decreased susceptibility to human errors compared to traditional methods of cognitive workload recognition. Consequently, it enables swift and accurate cognitive workload detection without direct human involvement.

TABLE IV. COMPARING THE PERFORMANCE OF OUR PROPOSED APPROACH WITH SOME STATE-OF-THE-ART STUDIES USING MACHINE LEARNING METHODS FOR MENTAL WORKLOAD IDENTIFICATION THROUGH EEG ANALYSIS

Reference	Dataset	Approach	Cross-validation	Accuracy (%)
[43]	28 EEGs from healthy adults during rest and task	Functional connectivity and SVM	LOSOCV	87.00
[22]	9 EEGs from healthy adults during rest and task	Time, frequency, and time-frequency features along with SVM	10-fold CV	84.00
[44]	8 EEGs from healthy adults during rest and task	Spectral features and stacked denoising autoencoder	Hold-out	74.00
[45]	7 EEGs from healthy adults during rest and task	Spectral features and adaptive stacked denoising autoencoder	Hold-out	85.79
[46]	15 EEGs from healthy adults during rest and task	Spectral features and MLP neural network	Hold-out	85.00
[47]	8 EEGs from healthy adults during rest and task	Time and frequency features, denoising autoencoder	Hold-out	86.00
[48]	12 EEGs from healthy adults during rest and task	Spectral features and neural network	Hold-out	75.00
[49]	20 EEGs from healthy adults during rest and task	Spectral and time features along with LDA	10-fold CV	90.00
[50]	22 EEGs from healthy adults during rest and task	Time and time-frequency features along with LDA	5-fold CV	70.00
Our proposed approach	36 EEGs from healthy adults during rest and task	Multifractal cumulants, differential entropy and various machine learning techniques	Hold-out	**96.52**

V. CONCLUSION

This research suggested two nonlinear features for mental workload recognition: multifractal cumulants and differential entropy. The multifractal cumulants feature captures the relationship between frequency bands, rather than quantifying the power within each specific band. This feature provides valuable information about the interplay between different frequency ranges. On the other hand, the differential entropy feature assesses the level of difficulty in predicting future EEG signal patterns based on their past behavior. This measure reflects the intricate dynamics present within the EEG signals. Surprisingly, our findings revealed that the multifractal cumulants and differential entropy can independently distinguish between different mental states as measured by EEG. Additionally, the obtained results demonstrated that combining these two features resulted in a higher accuracy of classification compared to solely utilizing each feature. Consequently, these new features are deemed valuable supplements to the existing features utilized in mental workload recognition, offering potential for enhanced this field. Future research may focus on exploring innovative methods for feature combination and selection, as well as extending the application of these features to multi-class problems beyond resting and task states. Moreover, it is essential to address the creation of new algorithms incorporating physiologically relevant error functions specifically tailored for EEG signal predictions involving the complexity feature. In addition, it is recommended that future studies use optimization algorithms such as genetic algorithm to adjust the parameters of nonlinear analyzes and FKNN classifier to improve the results and speed up the parameter adjustment process.

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