Local Pattern Descriptor-based EEG Classification During Mental Arithmetic Tasks: A Comparative Analysis of Machine Learning Models

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ABSTRACT
Cognitive neuroscience explores how brain functions relate to mental processes to better understand cognitive structures. To identify brain states linked to different mental activities, appropriate measurement tools are essential. In this study, a new framework is proposed for classifying mental workload and distinguishing between the resting state and mental counting using local pattern transformations and machine learning algorithms. Mental activities are analyzed using an Electroencephalogram (EEG) via three local pattern transformations: one-dimensional local binary patterns (1D-LBP), one-dimensional local gradient patterns (1D-LGP), and local neighbor descriptive patterns (LNDP). To classify cognitive workload (good vs. bad counters) and resting state versus mental counting, three classifiers are employed: gradient boosting (XGBoost), K-Nearest Neighbors (KNN), and random forests (RF). Using XGBoost and three feature extraction methods, an average performance of about 98% was achieved. With KNN, the highest accuracy was obtained, averaging 99% across all performance metrics with all three feature extraction methods. When using RF, the average score was around 99% with 1D-LBP and 1D-LGP, and 98% with LNDP.

General Terms
ML, EEG, LBP

Keywords
EEG, one-dimensional local binary pattern (1D-LBP), one-dimensional local gradient pattern (1D-LGP), local neighbor descriptive pattern (LNDP), mental arithmetic

1. INTRODUCTION
The human brain is the center of cognitive activity, and appropriate methods and measurements are still needed to identify the brain states during various mental activities [1]. Cognitive neuroscience studies brain activities related to both neurological and psychological functions, using various imaging techniques to gain a comprehensive understanding of behavior and cognitive processes [2]. The goal of cognitive neuroscience is to understand the basic mental structures that support cognitive functions [3]. Extensive research has been conducted to explore the characteristics of human brain function during mental arithmetic processes. The electroencephalogram (EEG) is a convenient method due to its high temporal resolution, noninvasiveness, affordability, and portability, with minimal setup time [4]. Therefore, it is highly useful for real-time clinical applications and preferred for recording EEG signals during mental arithmetic tasks.

The authors examined the complexity of brain activity and highlighted the importance of using suitable techniques to capture its nonlinear dynamics using the Discrete Wavelet Transform (DWT) method, achieving promising results in detecting transitions in EEG signals [5]. Moreover, they utilized spectral entropy as a valuable tool for distinguishing between EEG recordings obtained before and during mental arithmetic tasks. In this study, the authors analyzed EEG signals to understand disorders such as attention-deficit hyperactivity disorder, dyscalculia, or autism spectrum disorder, which can cause difficulty in learning or understanding arithmetic [6]. They estimated effective connectivity using Direct Transfer Function (DTF), direct DTF (dDTF), and Generalized Partial Directed Coherence (GPDC) methods to measure the causal relationships between different brain regions. They used hierarchical feature selection along with five other feature selection methods to choose features, and SVM was used for classification, reaching an accuracy of 89%.

In this research, local pattern transformation-based feature extraction methods are used to classify good and poor performance in mental arithmetic tasks. Moreover, different machine learning algorithms are used to classify the periods before and during mental arithmetic. Three local pattern transformations: one-dimensional local binary patterns (1D-LBP), one-dimensional local gradient patterns (1D-LGP), and local neighbor descriptive patterns (LNDP). Local binary patterns are widely applied for analyzing textures in 2D images [7, 8, 9]. A decade ago, LBP began to be used in one-dimensional signals, particularly in EEG signals, to classify seizure periods in epilepsy patients [10, 11, 12, 13]. They referred to this approach as one-dimensional local binary pattern (1D-LBP) to extract features from EEG signals, achieving high accuracy in the classification of EEG signals. Recently, two new local pattern transformation methods, LNDP and 1D-LGP, have been introduced and applied in the classification of epileptic EEG signals, achieving an average classification accuracy of 99.82% and 99.80%, respectively [12]. Most previous research used local pattern transformation-based features for classifying neurological disorders, especially epilepsy, where epileptic EEG signals have high amplitude compared to normal signals, making it easier for methods to detect these signals and achieve high accuracy. However, in this research, cognitive task EEG was used —specifically the mental arithmetic task —to classify good counts versus bad counts and before versus during the task, using three different transformation-based feature extraction methods with various machine learning algorithms.

2. DATASET DESCRIPTION

In this study, a publicly available EEG dataset was used for analysis. The dataset includes EEG recordings of subjects before and during performing mental arithmetic tasks [14, 15]. The EEGs were recorded with a Neurocom EEG 23-channel system, following the international 10/20 system. A high-pass filter with a 30Hz cutoff frequency and a 50Hz notch filter were applied. All recordings are artifact-free EEG segments of 60 seconds each. During data preprocessing, independent component analysis (ICA) was used to remove artifacts from eye movements, muscles, and cardiac activity. The data were recorded from 36 healthy participants (9 male and 27 female) aged 18 to 26 years (Mean = 18.6 years, standard deviation = 0.87 years). The arithmetic task involved serial subtraction of two numbers. Each trial began with an oral presentation of 4-digit (minuend) and 2-digit (subtrahend) numbers (e.g., 3141 and 42). The 36 subjects were divided into two groups: the proposed task was a difficult task for one group of participants (group “Bad”, 12 subjects, mean number of operations = 7, SD = 3,6), whereas the second group managed the task without difficulty (group “Good”, 24 subjects, mean number of operations = 21, SD = 7,4).

3. METHODOLOGY

The mental arithmetic EEG signals were used to classify good count and bad count. The EEG signal is extracted for the local pattern information using three different local pattern transformation methods, such as local binary pattern, local gradient pattern, and local neighbor descriptive pattern. Then, the machine learning algorithms are applied: gradient boosting (XGBoost), K-Nearest Neighbors (KNN), and random forests (RF). The overall framework of the mental arithmetic classification is shown in figure 1.

3.1 1D-local Binary Pattern (1D-LBP)

The 1D-LBP method was derived from the steps used in 2D-LBP and was proposed for detecting non-stationary speech signals [10]. For each data sample in a signal, a binary code is generated by comparing its value to that of the center sample. This process is repeated across the entire signal. The equation of 1D-LBP on a sample is given by:

$$P_c^{\mathrm{1D-LBP}} = \sum_{i=0}^{m-1} k(S_i - S_c)2^i \tag{1}$$

where

$$k(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases}$$

where m is the number of neighboring points, Si and Sc are the neighbor and center points of the segment.

3.2 1D-local Gradient Pattern (1D-LGP)

1D-LGP method preserves the structural property of a pattern [12]. The equation of the 1D-LGP is as follows:

(1) The gradient value is computed as $f_i = |S_i - S_c|$, for $i = 0, \ldots, m-1$, where m is the number of neighboring points

(2) The mean gradient value is computed as follows:

$$f_{avg} = \frac{1}{m}\sum_{i=0}^{m-1} f_i \tag{2}$$

(3) Compute the gradient code as $fc_i = |f_i - f_{avg}|$, for $i = 0, \ldots, m-1$.

$$P_c^{\mathrm{1D-LGP}} = \sum_{i=0}^{m-1} k(fc_i)2^i \tag{3}$$

where

$$k(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases}$$

3.3 Local Neighbor Descriptive Pattern (LNDP)

LNDP is a feature extraction technique that relies on local pattern transformation, capturing the relationships between neighbors and preserving the pattern's structural properties by comparing the values of neighboring points within the pattern [12].

(1) The difference of consecutive points is computed as: $n_i = s_i - s_{i+1}$, for $i = 0, \ldots, m-1$, where m is the number of neighboring points.

(2) Computed the LNDP by

$$P_c^{\mathrm{LNDP}} = \sum_{i=0}^{m-1} k(n_i)2^i \tag{4}$$

where

$$k(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise \end{cases}$$

The values of local pattern transformation from raw EEG signals using three methods are shown in figure 2. The raw EEG recordings, taken while a participant was resting and performing mental counting, are displayed in figure 2(a) and 2(b). When applying 1D-LBP to the signals and the decimal values from both states, resting and mental counting, the values range from 0 to 255. The histogram’s distribution is

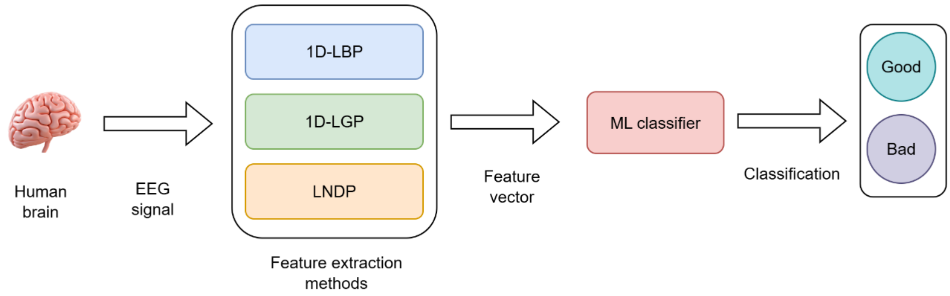
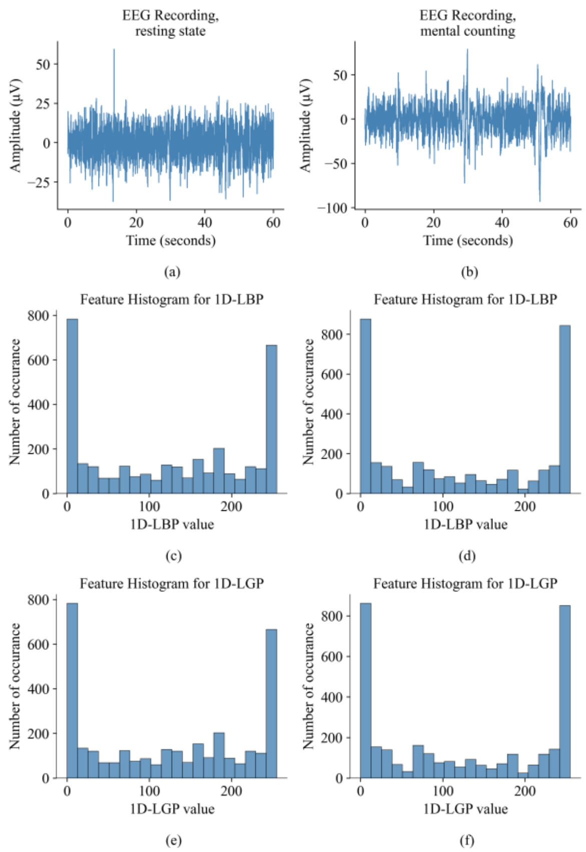


Fig 1: Overall framework for mental arithmetic classification

shown in figure 2(c) and 2(d). Again, the distribution reflects the 1D-LGP, with LNDP also illustrated in figure 2(e-h). After analyzing features from these three methods, different classification techniques are used to categorize the two types: good count and bad count, as well as resting state and during mental counting.

For the classification stage, three algorithms are applied: XGBoost, KNN, and RF. Before the classification stage, the features from all 36 participants (grouping together) are concatenated to classify the good vs bad, and the features from before and during the tasks are concatenated for classification of the resting state and mental counting. The feature data is split into training and testing with an 80-20 ratio. The training set is applied to the SMOTE Imbalance Learn package [17] to balance the positive (good count and mental counting) and negative classes (bad count and resting state). However, the SMOTE did not apply for the test set. The 5-fold cross-validation was performed at both the participant and group levels with hyperparameter tuning using HalvingGridSearchCV [18] for all machine learning models.



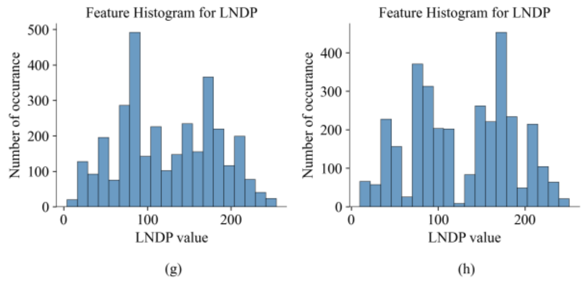


Fig 2: Feature extraction from local pattern transformation, (a) a segment of the EEG signal (resting state), (b) a segment of the EEG signal (mental counting), (c) histogram of 1D-LBP (resting state), (d) histogram of 1D-LBP (mental counting), (e) histogram of 1D-LGP (resting state), (f) histogram of 1D-LGP (mental counting), (g) histogram of LNDP (resting state), and (h) histogram of LNDP (mental counting)

4. RESULTS AND DISCUSSION

As mentioned above, using the 5-fold cross-validation technique, the best classification accuracy was achieved, 98.25% with 1D-LBP + KNN, along with a precision of 98.28% with 1D-LBP + KNN, a recall of 98.25% with 1D-LBP + KNN, and an F1-score of 98.25% with 1D-LBP + KNN (see table 1). From tables 2 and 3, the best performance metrics for KNN were achieved on both 1D-LGP and LNDP, with results exceeding 98% and 97%, respectively. Therefore, this study demonstrates that these three feature extraction methods perform well in differentiating between good and bad counts with various classifiers, with all performance metric scores above 90%. The accuracy, precision, recall, and F1-score are defined as:

- Accuracy: The ratio of correctly predicted classes (both positive and negative) to the total number of classes, the formula is (TP+TN)/(TP+TN+FP+FN).
- Precision: Out of all classes the model predicted as positive, how many were actually positive, the formula is TP/TP+FP.
- Recall: Out of all the actual positive classes in the data, how many did the model correctly identify, the formula is TP/(TP+FN).
- F1-score: A single metric that balances precision and recall by calculating their harmonic mean, the formula is 2×(Precision×Recall)/(Precision+Recall).

Where TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

Table 1. Classification report for 1D-LBP and three machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
XGBoost	92.58	92.63	92.58	92.60
KNN	98.25	98.28	98.25	98.25
RF	97.27	97.29	97.27	97.24

Table 2. Classification report for 1D-LGP and three machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
XGBoost	92.50	92.51	92.50	92.50
KNN	98.18	98.22	98.18	98.19
RF	97.22	97.23	97.22	97.19

Table 3. Classification report for LNDP and three machine learning models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
XGBoost	92.72	92.65	92.72	92.67
KNN	97.11	97.21	97.11	97.13
RF	95.80	95.87	95.80	95.72

After the group-level classification, the individual-level classification was performed for the resting state versus the mental counting condition. Three features were extracted—1D-LBP, 1D-LGP, and LNDP—from 36 participants and input these features into different classifiers for classification. In figure 3, XGBoost was used, and three feature extraction methods were used, achieving an average of around 98% across all performance measures. With KNN, the best score was achieved, averaging 99% across all performance metrics in all three feature extraction methods (see figure 4). RF was used for classification, and the average score of the performance matrix was around 99% with 1D-LBP and 1D-LGP, and 98% with LNDP, as shown in figure 4. The overall performance score of each participant is illustrated, which is shown in figure 3-5. An average classification performance score of 98% was achieved using three feature extraction methods and three different classifiers. As previous research reports 99% in LBP, 99.80% in 1D-LGP, and 99.82% in LNDP, when classifying epileptic EEG signals [10, 12]. Epileptic EEG signals typically contain high-amplitude, stereotyped events that are readily separable from normal activity, whereas mental arithmetic tasks involve more subtle, distributed modulation in local texture features. However, this research achieved a similar score to that of the previous study, despite using a different cognitive task dataset. The computational efficiency of all local pattern transformation methods averages 0.33 seconds for 1D-LBP, 0.35 seconds for 1D-LGP, and 0.45 seconds for LNDP, as shown in figure 6. All experiments are conducted using Python and are executed on an 11th Gen Intel® Core™ i7-1195G7 (2.92GHz) CPU machine with 16 GB RAM. All machine learning models run exclusively on the CPU.

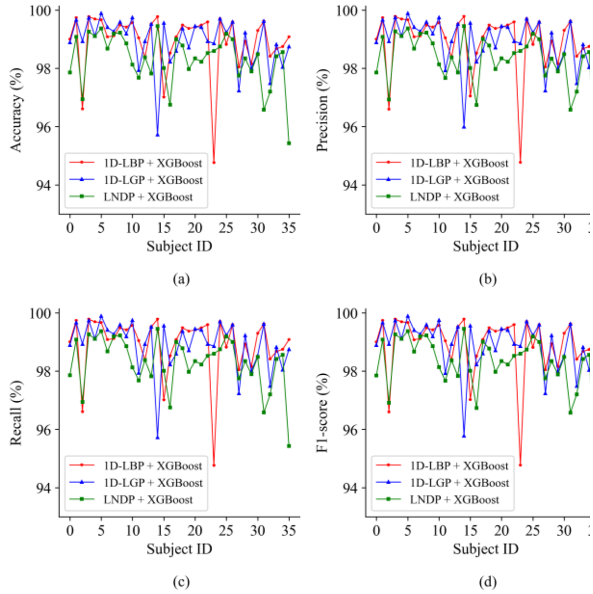


Fig 3: Classification report of three feature extraction methods with XGBoost (a) accuracy, (b) precision, (c) recall, and (d) f1-score

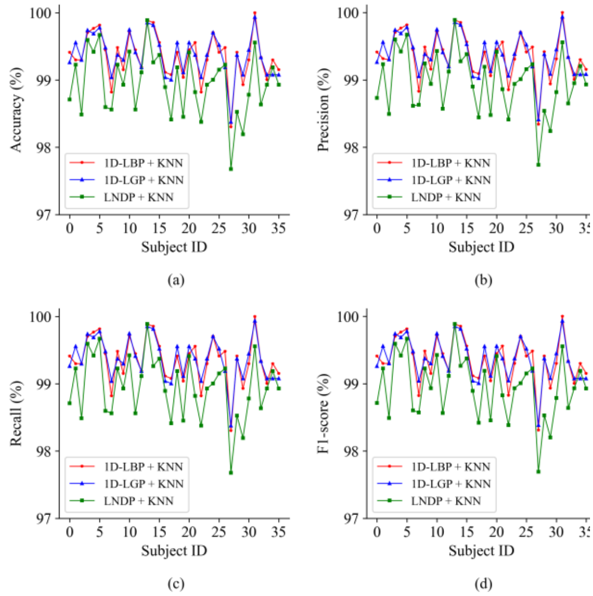
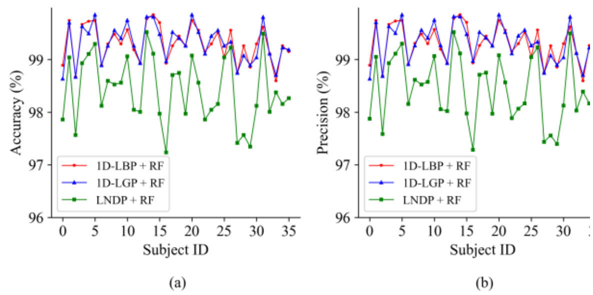


Fig 4: Classification report of three feature extraction methods with KNN (a) accuracy, (b) precision, (c) recall, and (d) f1-score



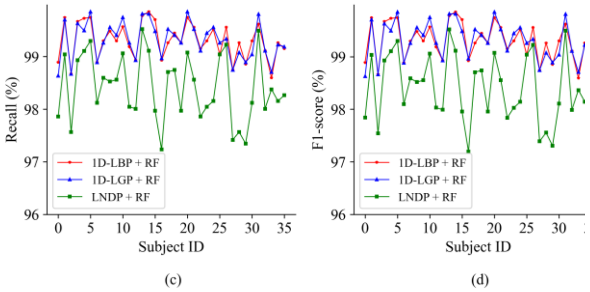


Fig 5: Classification report of three feature extraction methods with RF (a) accuracy, (b) precision, (c) recall, and (d) f1-score

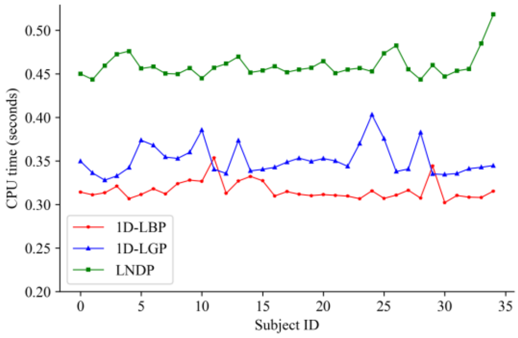


Fig 6: Comparison of three local pattern transformation methods in terms of the CPU time

5. CONCLUSION

In this study, a novel framework for classifying mental states was developed using three local pattern features: 1D-LBP, 1D-LGP, and LNDP, combined with three classifiers—XGBoost, KNN, and RF. XGBoost was used with three feature extraction methods, achieving an average accuracy of around 98% across all performance measures. KNN yielded the highest score, averaging 99% across all metrics for all three feature extraction methods. When using RF for classification, the average performance score was about 99% with 1D-LBP and 1D-LGP, and 98% with LNDP. Overall, an average classification accuracy of 98% was achieved using three extraction methods and three different classifiers. For future research, it is necessary to explore features across different EEG frequency bands and brain regions that may contribute more significantly to cognitive workload. Additionally, it is necessary to analyze different datasets using the same framework in this research to assess the performance of local pattern transformation methods.

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