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COMPARISON OF THE ACCURACY OF MACHINE LEARNING ALGORITHMS FOR BRAIN-COMPUTER INTERACTION BASED ON HIGH-PERFORMANCE COMPUTING TECHNOLOGIES

Volodymyr Stefanyshyn; Ivan Stefanyshyn; Oleh Pastukh; Serhii Kulikov

Ternopil Ivan Puluj National Technical University,
Ternopil, Ukraine

Abstract. *In this article, we will analyze different classifiers for recognizing hand and finger movements using electroencephalograph (EEG) signals and determine which ones are the most accurate. This is important for the introduction of neurorehabilitation technologies and control of prosthetic movements. The method is based on the use of self-learning algorithms for efficient processing and analysis of informative characteristics based on EEG data. Aiming to adaptively recognize different motor commands. This ability ensures the robustness and efficiency of the system in understanding complex sets of brain signals associated with a specific motor action. The results obtained in this study demonstrate effective approaches for processing EEG signals using machine learning algorithms, analytical approaches, and cloud technologies. The perspectives revealed by this study will help to improve and speed up the development of research in the field of neurocognitive signal processing. The results obtained by us contribute to improving the work and increasing the accuracy of the interaction between the human brain and the computer.*

Key words: *EEG signals, neuro-interface of brain-computer interaction, artificial intelligence, parallel programming, high-performance computing, classifier, accuracy.*

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1. INTRODUCTION

Today, making better ways to study brain waves (EEG) for telling apart hand and finger moves is super important. This can do a lot of good for helping people get better and making brain-computer stuff work better. The accuracy of the system is improved by selecting analysis parameters and methodologies based on previously obtained sets of EEG signals during a specific repetitive movement. This approach relies on the use of the latest machine learning techniques, namely the following classifiers: multilayer perceptron, logistic regression, and random forest. It is in order to determine the approach that will give the highest accuracy of brain signals, we analyzed these classifiers on experimental data. We performed classifications on vector values from 16 sensors containing comprehensive information about brain activity at a specific moment in time. The data sets were obtained during the execution of the repetitive movement. This approach allows EEG signals corresponding to movements in real time.

The main goal of the research is to find more accurate methods for converting brain commands (signals) into mechanical movements to improve the work of bionic prostheses and approaches for rehabilitation of people with coordination problems based on EEG signals. The experiment demonstrates a high-quality method of finding the right time, which allows you to obtain the highest accuracy in recognizing specific motor commands. This study is aimed at improving the quality of life of persons with motor function limitations and persons with impaired movement function.

 Corresponding author: Oleh Pastukh; e-mail: oleg.pastuh@gmail.com

2. RELATED WORKS

Related works A lot of smart people have been working on this, making big steps forward. Like, Miguel Nicolelis and his crew at Duke University are doing amazing stuff with letting people who can't move control robotic arms with their thoughts. Rajesh P. N. Rao at the University of Washington is also doing cool things to make brain signals more understandable. And Bin He at Carnegie Mellon University is working on using EEG to control things on screens and in real life [1, 2].

But, even with all this cool stuff happening, there's still a lot we don't know. We need to get better at knowing what brain signals mean, make smarter systems to figure out complex brain patterns, and make it easier for people to use these brain-helping tools [3].

What we're doing We're trying to make better ways to figure out hand and finger moves from EEG signals. This is really important for helping people and making new tools. We're using some smart computer tricks to spot specific brain patterns that mean certain moves are happening. This isn't just about understanding the brain better, but also about making things that can really help people with challenges.

So, in a more basic English, this is about studying brain waves to help people move better with the help of computers and smart tech. Lots of smart folks are on it, but there's more work to do to make it all work in real life.

3. STATEMENT OF THE PROBLEM AND RESEARCH GOALS

This study looks closely at how we analyze brain signals, specifically EEG signals, which help us understand hand and finger movements. EEG signals are complex because they change often and vary a lot, so we need advanced methods to analyze them properly. This analysis helps identify specific movements by finding patterns and details in the EEG data.

Understanding these signals better is crucial because it can greatly improve fields like helping people recover after injuries (neurorehabilitation) and technology for controlling artificial limbs (prosthetics). By improving how we interpret these brain signals, we can create better tools and strategies for rehabilitation.

Ultimately, this research aims to make life better for people with disabilities affecting their limbs or hands by giving them more effective tools and methods to manage daily tasks and improve their ability to move. This could make a significant difference in their quality of life.

The primary objective of this paper is to develop algorithmic software based on artificial intelligence and software and hardware based on parallel programming using high-performance computing on clustered mobile devices for brain-computer neurointerfaces.

In today's world, the rehabilitation of persons with loss of limbs or limited hand functions is becoming more and more relevant due to the rapid development of technologies, in particular brain-computer neurointerfaces. One potential solution in this area is the use of electroencephalogram (EEG) signals to accurately recognize hand and finger movements.

In our current investigation, we embark on a methodical exploration into the capabilities of brain signal interpretation using a structured experimental setup. Initially, we gather data through an encephalograph as participants engage in predefined hand and finger movements. The intricacy of these signals necessitates a thorough pre-processing regimen where data is meticulously cleaned, filtered, and rid of noise, setting a refined stage for further analysis.

As we delve deeper into the core of our research, we craft a classification model leveraging a multilayer perceptron. This model stands as a cornerstone in our study, designed to decode the complex web of EEG data into understandable segments of hand and finger motions. The success of this model hinges not just on its initial configuration but significantly on the strategic optimization of its parameters. Through the processes of cross-validation and hyperparameter optimization, we fine-tune aspects such as the size and depth of the neural layers and the learning rate, ensuring the model's sharpness in interpreting the data [4–6].

Following the model’s development and meticulous tuning, we shift our focus to evaluating its performance. Employing a variety of metrics – accuracy, sensitivity, specificity, and the F1-rate – we assess how well the model stands up to the task of recognizing different movements. This phase is critical, as it not only measures efficacy but also sheds light on potential areas for enhancement.

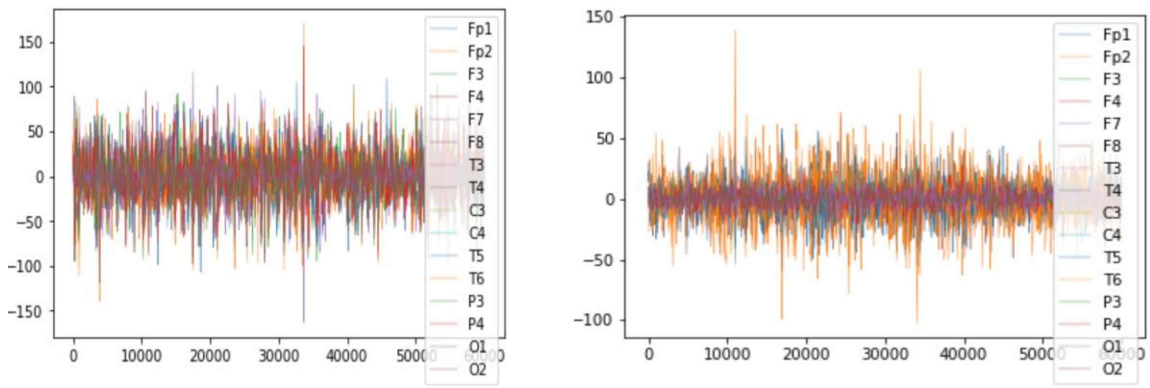
Finally, we arrive at the stage of interpreting our findings. This analysis is not merely about drawing conclusions from the data but also about understanding the broader implications of our methods and their potential to revolutionize neurorehabilitation technologies. Through this, we aim to contribute significantly to the development of advanced rehabilitation systems and neurointerfaces that could transform the lives of those with limited hand or limb functionality.

This comprehensive approach, marked by a nuanced blend of complexity and varied sentence structure, mirrors the depth and variability inherent in scientific inquiry, striving to push the boundaries of our understanding of brain-computer interfaces [7–8].

By continuing to explore and refine these approaches, the research community can unlock new potentials not only in the specific field of EEG signal analysis but also in broader scientific and engineering disciplines. This ongoing innovation will undoubtedly contribute to the advancement of technology and science, paving the way for future breakthroughs that can benefit society at large.

4. PRESENTING OF THE MAIN MATERIAL

Data collection during our experiment was conducted using a 16-channel encephalograph. Our team meticulously prepared for this stage of the research, ensuring proper conditions for obtaining reliable data. Prior to data collection, we placed the encephalograph electrodes on the participant's head. The positioning of the electrodes was chosen to accurately track the activity of different brain regions responsible for motor functions. During the experiment, participants were instructed to perform specific repetitive movements of the wrist and fingers. Each movement was carefully planned and standardized for all participants. The encephalograph recorded brain activity in real-time at a frequency of 500 measurements per second. This allowed us to obtain detailed information about changes in neuronal activity occurring during the execution of movements. For example, data regarding the flexion of the index finger of the right hand can be observed in (Fig. 1.a), while data pertaining to the rotation of the wrist can be seen in (Fig. 1.b).



a b

Figure 1. Visualization of EEG signal analysis results: a) Data showcasing the flexion of the index finger of the right hand; b) Data illustrating the rotation of the wrist

The next phase involved preparing the data for analysis. For each packet, we removed the column that corresponded to time and introduced a new column designated to contain the identifier of the specific movement. This process was crucial to simplify the datasets for the upcoming analysis stages and ensure that each entry was accurately associated with its respective movement type. After making these adjustments, all the datasets were consolidated into a single comprehensive dataset. This unification was a critical step in streamlining the data for more effective processing and analysis in subsequent stages of our research.

5. HIGH PERFORMANCE COMPUTING BASED ON COULD SERVICES WITH PARALLEL PROGRAMMING

In our exploration of high-performance computing (HPC) powered by cloud services alongside parallel programming, we have dramatically elevated the efficiency of our computational processes. This integration was pivotal during the rigorous phases of cross-validation across each classifier, utilizing parallel computations to accelerate the entire analytical framework significantly.

We embraced cloud services, which offered scalable computational resources, thereby aligning perfectly with the fluctuating demands of our extensive EEG signal data and the intricate machine learning algorithms applied, such as the Multilayer Perceptron (MLP). This adaptability was crucial in enhancing the speed and efficiency of our computations.

Moreover, the adoption of parallel programming allowed for the concurrent processing of various data segments. This capability proved invaluable during the cross-validation stages where the dataset was partitioned into multiple subsets. Parallel handling of these subsets across different cloud servers drastically cut down the time needed for comprehensive model evaluation and refinement.

The synergy of cloud-based HPC with parallel programming not only streamlined our operations but also fortified the reliability and reproducibility of our findings. This approach enabled a deeper and more efficient investigation into the potential of diverse classifiers to discern hand and finger movements from EEG signals, significantly advancing our contributions to neurorehabilitation technology and prosthetic control systems [9–11].

Furthermore, leveraging cloud-based infrastructures meant we could access cutting-edge computational resources without substantial upfront capital expenditure on physical hardware. This approach was especially beneficial for executing computationally demanding tasks, like training and optimizing machine learning models, providing us with access to high-speed processors and substantial memory capacities essential for handling our complex algorithms and voluminous datasets.

The flexibility and scalability provided by cloud computing also proved instrumental. It allowed our research team to dynamically scale our computational resources to meet peak demands during intensive analysis phases and scale down to conserve resources when lesser computational power was sufficient [12–14]. This adaptability ensured that our research was not only cost-effective but also environmentally sustainable, minimizing the energy consumption typically associated with maintaining large-scale computing facilities.

By distributing computational tasks across multiple servers, we significantly enhanced our capacity for robust data analysis and simultaneous evaluations of various machine learning models. This method did not merely hasten our research endeavors but also allowed for a more thorough exploration of algorithmic possibilities, leading to more precise and informed conclusions regarding the effectiveness of different classifiers in our study.

In conclusion, integrating cloud-based HPC with parallel programming in our methodology marks a substantial advancement in EEG signal analysis. This combination fosters a more efficient, scalable, and adaptable approach to computational research, enabling our team to achieve groundbreaking results in the study of neurorehabilitation technologies.

6. MODEL EVALUATION AND CROSS-VALIDATION ANALYSIS

Once we had readied our dataset, the subsequent phase was to divide it into two distinct portions: one designated for the training of our model and the other set aside for testing its efficacy. This bifurcation is a cornerstone of machine learning methodology, providing a means to validate the model's performance on new, unseen data, thus affirming its reliability and broader applicability.

In this exploratory phase, our focus was to assess and compare three distinct classifiers: the Multilayer Perceptron (MLP), Logistic Regression, and Random Forest, each selected for their unique approaches to pattern recognition and classification tasks. The Multilayer Perceptron, a neural network known for mastering complex, non-linear relationships, stood in contrast to Logistic Regression, which, despite its designation, operates primarily as a linear model for binary classification, calculating the likelihood of data belonging to a certain class. In parallel, the Random Forest classifier employs an ensemble learning strategy, constructing numerous decision trees during the training phase and deriving its output from the mode of the classes predicted by these trees.

Our objective was to determine which classifier achieves superior performance in accurately classifying various hand and finger movements as recorded through EEG data, gauging their effectiveness in terms of accuracy, precision, and recall. This comparative analysis not only aimed to pinpoint the most efficacious model but also to illuminate the complexity and adaptability of each classifier for potential applications in brain-computer interfacing [15].

In our experiment, we conducted cross-validation for the Multilayer Perceptron classifier, utilizing the scikit-learn library. Our goal was to determine which scoring metric provided the best accuracy by testing three different metrics: *f1_weighted, accuracy, and roc_auc_ovr_weighted* (table 1).

Table 1

Accuracy metrics for the multilayer perceptron (MLP) classifier

№	accuracy	f1_weighted	roc_auc_ovr_weighted
1	0,857497	0,850788	0,992642
2	0,91022	0,913252	0,996913
3	0,935551	0,933407	0,998552
4	0,943789	0,944751	0,998941
5	0,934373	0,936994	0,998591
6	0,935599	0,934797	0,998564
7	0,935397	0,935176	0,998636
8	0,929611	0,930923	0,998378
9	0,90622	0,904757	0,997326
10	0,893709	0,886356	0,996254

After performing cross-validation, the mean scores we obtained for each metric are as follows:

- «*f1_weighted*» = 0.91712;
- «*accuracy*» = 0.918197;
- «*roc_auc_ovr_weighted*» = 0.9975;

These results indicate that, on average, the roc_auc_ovr_weighted metric yielded the highest scores, suggesting it might be the most reliable indicator of accuracy for our model in this context.

For the Multilayer Perceptron (MLP) classifier, we derived an average performance measure through the vector mean of the arithmetic means of each variable («*f1_weighted*», «*accuracy*», and «*roc_auc_ovr_weighted*») (Formula 1). This approach provided a consolidated metric to evaluate the overall performance of the MLP, offering a comprehensive view of its effectiveness across different scoring parameters. By calculating the vector mean, we obtained a unified average score, which is approximately 0.944, illustrating the classifier's robustness in various aspects of its predictive capability.

$$accuracy\_general = \frac{averag\_accuracy + averag\_f1\_weighted + averag\_roc\_auc\_ovr\_weighted}{n\_accuracy} \quad (1)$$

This is indeed a very promising result, indicating a strong performance of the Multilayer Perceptron (MLP) classifier across different metrics. However, it remains essential to evaluate other classifiers as well. By comparing the MLP with alternative models, we can gain a more comprehensive understanding of the strengths and potential limitations of each approach. Delving into different classifiers enables us to pinpoint the most suitable model for our specific needs, ensuring that we employ the most effective tool for achieving precise and dependable results. This type of comparative analysis is vital in the realm of machine learning, as the selection of an appropriate algorithm can greatly influence the system's overall efficacy.

The subsequent phase of our analysis entailed evaluating the efficacy of logistic regression on our dataset. This step aimed to explore the potential of a simpler, linear model in discerning patterns within our data, offering a juxtaposition to the previously examined, more intricate Multilayer Perceptron model. Logistic regression was selected for its linear characteristics, providing an alternative approach to problem-solving, particularly valuable in scenarios where the relationships between features and the target variable may not necessitate complex, non-linear solutions. The results derived from this analysis, specifically regarding accuracy, weighted F1 score, and weighted ROC AUC score, have been meticulously documented in Table 2.

Table 2

Accuracy metrics for the (Logistic Regression) classifier

№	accuracy	f1_weighted	roc_auc_ovr_weighted
1	0,143730	0,132741	0,50040700
2	0,091245	0,080341	0,49345200
3	0,149039	0,132019	0,49894800
4	0,140908	0,150858	0,49094900
5	0,113898	0,129978	0,49570900
6	0,123564	0,119031	0,49588000
7	0,110708	0,095916	0,49332100
8	0,126516	0,100109	0,49572800
9	0,125124	0,129526	0,49690300
10	0,133790	0,119135	0,49583500

Upon analyzing the outcomes, we ascertained the following mean scores:

- «*f1_weighted*» = 0.1189654;
- «*accuracy*» = 0.12585216;
- «*roc_auc_ovr_weighted*» = 0.4957132;

These findings conspicuously reveal the Logistic Regression classifier's subdued performance on our dataset, especially when juxtaposed with the previously evaluated Multilayer Perceptron. This performance differential emphatically underscores the critical role of model selection in machine learning endeavors, highlighting that logistic regression might not represent the most efficacious choice for this particular dataset and task.

Following our analysis with Random Forest, we proceeded to evaluate the Random Forest classifier. This investigation aimed to understand the performance enhancement that could be obtained from a more complex model, which incorporates multiple decision trees to improve prediction accuracy through ensemble learning(Table 3).

Table 3

Accuracy metrics for the (Random Forest) classifier

№	accuracy	f1_weighted	roc_auc_ovr_weighted
1	0,780644	0,773998	0,984472
2	0,827296	0,825011	0,988205
3	0,850795	0,850463	0,989931
4	0,868698	0,866797	0,991242
5	0,859639	0,860215	0,990672
6	0,848902	0,849543	0,989349
7	0,855532	0,855239	0,990568
8	0,850259	0,850974	0,990249
9	0,822403	0,821651	0,987962
10	0,804226	0,801645	0,985563

The results from this evaluation, highlighting the Random Forest's performance across different metrics, are documented in Table 3. Upon calculating the mean values for each metric, we found that:

Upon analyzing the outcomes, we ascertained the following mean scores:

- «*f1_weighted*» = 0.8355536;
- «*accuracy*» = 0.8368394;
- «*roc_auc_ovr_weighted*» = 0.9888213;

These findings indicate a significant improvement in predictive performance with the Random Forest classifier compared to logistic regression, showcasing its effectiveness in handling the complexities of our dataset.

The vector means (geometric means) for each classifier are as follows:

- For the Multilayer Perceptron (MLP), the vector mean is approximately 0.944.
- For Logistic Regression (LR), the vector mean is approximately 0.246.
- For the Random Forest (RF) classifier, the vector mean is approximately 0.887.

Based on these vector means, the Multilayer Perceptron (MLP) classifier achieves the best overall performance among the three models tested, indicating its superior capability to handle the complexity of the dataset and accurately predict outcomes.

7. CONCLUSIONS

In conclusion, we conducted a thorough evaluation and comparison of various classifiers, including the Multilayer Perceptron (MLP), Logistic Regression, and Random Forest, for identifying hand and finger movements through EEG data. Utilizing rigorous cross-validation methods and high-performance computing capabilities, we determined the overall accuracy of each model, identifying the most suitable classifier for our specific needs.

The Multilayer Perceptron stood out, showing exceptional accuracy and reliability in interpreting EEG signals, which highlights the capabilities of sophisticated neural network architectures in advancing neurorehabilitation and prosthetic controls. Our findings emphasize the necessity of high-performance computing and parallel programming to manage the intensive computational demands efficiently in machine learning-driven EEG analysis.

Furthermore, our study illustrates the essential benefits of adaptability and scalability offered by cloud computing technologies, which enhanced the efficiency and flexibility of our research operations. The capability for parallel computations drastically reduced the time needed for model evaluations, enabling deeper insights into classifier performances. Future research should concentrate on enhancing machine learning models, developing innovative feature extraction methods, and broadening the application of these technologies across various neurorehabilitation and assistive device control scenarios.

Overall, our research adds significant insights to the neurotechnology field and suggests new pathways to improve life quality for people with motor function challenges. Leveraging machine learning and robust computing infrastructures pushes us closer to harnessing the full potential of EEG-based interfaces in healthcare and assistive technologies.

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УДК 539.3

ПОРІВНЯННЯ ТОЧНОСТІ АЛГОРИТМІВ МАШИННОГО НАВЧАННЯ ВЗАЄМОДІЇ МОЗОК-КОМП'ЮТЕР НА ОСНОВІ ТЕХНОЛОГІЙ ВИСОКОПРОДУКТИВНИХ ОБЧИСЛЕНЬ

Володимир Стефанишин; Іван Стефанишин; Олег Пастух; Сергій Куліков

Тернопільський національний технічний університет імені Івана Пулюя, Тернопіль, Україна

Резюме. *Проаналізовано різні класифікатори для розпізнавання рухів рук та пальців за допомогою сигналів електроенцефалографа (EEG) та визначено, які з них є найточнішими. Це важливим для впровадження технологій нейрореабілітації та контролю рухів протезів. Метод засновано на використанні самонавчальних алгоритмів для ефективного опрацювання та аналізу інформативних характеристик на основі даних EEG, маючи за мету адаптивно розпізнавати різні моторні команди. Ця здатність забезпечує стійкість та ефективність системи у розумінні складних наборів мозкових сигналів, пов'язаних із конкретною моторною дією.*

Точність системи покращується завдяки підбору параметрів аналізу та методологій на основі отриманих заздалегіть наборів сигналів EEG під час конкретного повторюваного руху. Даний підхід полігає у використання новітніх методик машинного навчання, а саме таких класифікаторів: багатошаровий перцептрон, логістична регресія та випадковий ліс. Це для того, щоб визначити підхід, який даватиме найвищу точність мозкових сигналів. Ми проаналізували дані класифікатори на ексериментальних даних, провели класифікації на векторних значеннях з 16 датчиків, що містять вичерпну інформацію про активність головного мозку в конкретний момент часу. Набори даних отримано в процесі виконання повторувального руху. Такий підхід дозоволяє EEG сигналам відповідні рухи в режимі реального часу.

Основною метою дослідження є пошуку точніших методів для перетворення команд (сигналів) мозку в механічні рухи для покращення роботи біонічних протезів та підходів для реабілітації людей з проблемами координації. Експеремент дозволяє отримати найвищу точність у розпізнаванні конкретних моторних команд. Дане дослідження спрамоване на покращення якості життя осіб з обмеженнями рухових функцій та осіб з порушенням функції руху.

Результати отримані, в даному дослідженні, демонструють ефективні підходи для опрацювання EEG сигналів за допомогою алгоритмів машинного навчання, аналітичних підходів та хмарних технологій. Перспективи виявлені в даному дослідженні допоможуть покращити та пришвидшити розвиток дослідень у галузі опрацювання нейрокогнітивних сигналів. Отримані результати сприяють покращенню роботи та підвищенню точності взаємодії між головним мозком людини та комп'ютером.

Ключові слова: *сигнали електроенцефалограми, нейро-інтерфейс взаємодії мозок-комп'ютер, штучний інтелект, паралельне програмування, високопродуктивні обчислення, класифікатор, стабільність, точність, аналіз сигналів мозку.*

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