Вісник Тернопільського національного технічного університету
https://doi.org/10.33108/visnyk_tntu
Scientific Journal of the Ternopil National Technical University
2023, № 4 (112) https://doi.org/10.33108/visnyk_tntu2023.04
ISSN 2522-4433. Web: ***visnyk.tntu.edu.ua***

UDC 681.3

BRAIN-COMPUTER INTERACTION NEUROINTERFACE BASED ON ARTIFICIAL INTELLIGENCE AND ITS PARALLEL PROGRAMMING USING HIGH-PERFORMANCE CALCULATION ON CLUSTER MOBILE DEVICES

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Summary. *The paper deals with hardware and software support for the interaction of human brain activity with the dynamic movement of the part of its upper limb based on artificial intelligence and its parallel programming using high-performance computer calculation on cluster mobile devices. The obtained results can be used as a basis for the development of high-performance software and hardware for the effective operation of brain-computer interaction neuro interfaces.*

Key words: *neuro interface of brain-computer interaction; artificial intelligence; parallel programming; high-performance computing, cluster mobile devices.*

https://doi.org/10.33108/visnyk_tntu2023.04.026 *Received 09.10.2023*

Statement of the problem. The development of various types of neural interfaces for brain-computer interaction is an urgent scientific problem.

The solution to this problem will make it possible to eliminate the daily suffering for those people who experienced certain injuries to their bodies. For example, they can use various kinds of bionic limb prostheses in case of loss of their own limbs, restore control over parts of their own body in case of spinal cord injuries, etc.

Furthermore, the development of neural interfaces for brain-computer interaction makes it possible to expand the functional abilities of human beings in terms of augmented and virtual realities application.

Analysis of the available investigation research results. Since at present there is an exponential increase in the number of investigations focused on the development of neural interfaces for brain-computer interaction, we will mention as the examples only the most famous ones. They include research by neurotechnology companies: «Neuralink» by Elon Musk [1] and Brian Johnson's «Kernel» by Brian Johnson [2]. They develop invasive and non-invasive brain-computer interfaces, respectively.

For the sake of justice, we note a number of promising results obtained in this area, which are published in papers [3–11].

The objective of the paper is to develop algorithmic software based on artificial intelligence and software – hardware based on parallel programming using high-performance computer calculations on cluster mobile devices for neurointerfaces of brain-computer interaction.

Statement of the problem. One of the important components in the development of brain-computer neurointerfaces is the application of algorithmic and software - hardware. Their importance is due to the fact that they determine the quantitative values of the quality metrics of brain-computer interaction neurointerfaces, such as, the values of accuracy, reliability, robustness, computational complexity, etc.

Improvement of these quantitative metrics: accuracy, reliability, robustness, computational complexity, etc. is possible with the development of algorithmic software based on modern artificial intelligence approaches and software – hardware based on parallel programming using high-performance calculation on cluster mobile devices.

Thus, the development of algorithmic software based on artificial intelligence and software – hardware based on parallel programming using high-performance computer computing on cluster mobile devices for neurointerfaces of brain-computer interaction is an important scientific and practical task.

Presenting of the main material. The material of this paper is based on practical results obtained on the basis of experiments.

The essence of the carried out experiments was as follows. The movement of the left thumb was performed during two minutes and at this moment the electrical activity of the brain was recorded on the basis of electroencephalographic (EEG) signals (Fig. 1). Then, the movement of the right thumb was performed during two minutes and at this moment the electrical activity of the brain was recorded on the basis of EEG signals as well (Fig. 2).

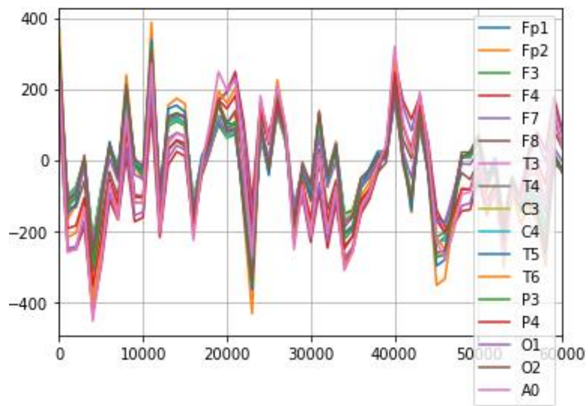

Figure 1. Visualization of EEG signals caused by the movement of the thumb of the left hand

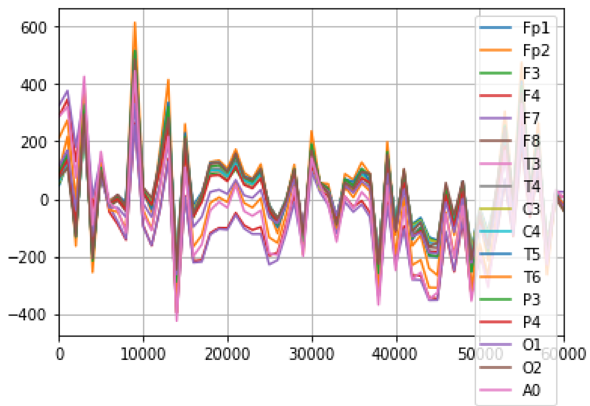

Figure 2. Visualization of EEG signals caused by the movement of the thumb of the right hand

For visualization, the schematic illustration of EEG signals selection is shown in Fig. 3 [12].

In order to select EEG signals, 16-channel electroencephalographic complex NEYROCOM produced by medical equipment manufacturer HAI-MEDICA was used in the investigation (Fig. 4) [13].

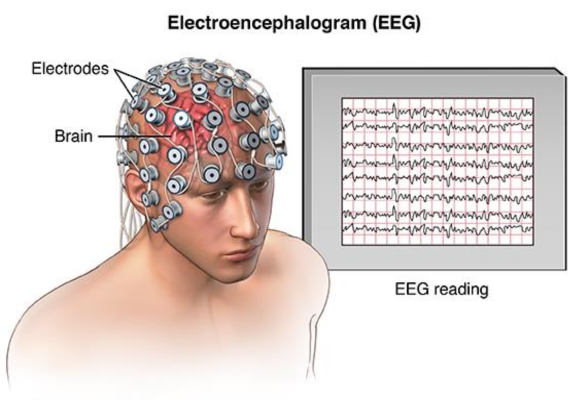

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Figure 3. EEG and brainwaves [12]

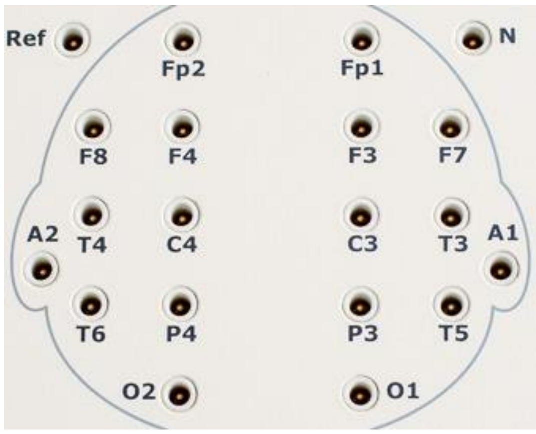

Figure 4. 16-channel electroencephalographic complex NEYROCOM produced by medical equipment manufacturer HAI-MEDICA [13]

Further, we considered the task of binary classification. The neurointerface of brain-computer interaction should decode EEG signals generated by the brain at the moments of the left and right thumb movements. Then the neurointerface of brain-computer interaction should transmit the output data to the microcontrollers of the left and right bionic prostheses for performing movements with the prosthetic thumbs of the left and right hands.

The binary classification task was solved by means of artificial intelligence algorithm, namely, the ensemble random forest algorithm. Thus, the ensemble random forest algorithm was used as the basis of the operation of the brain-computer interaction neural interface.

The input data for the ensemble random forest algorithm were EEG signals, and the output data were «0» codes for left thumb movement and «1» for right thumb movement.

The deployment of the ensemble random forest algorithm and software - hardware based on parallel programming using high-performance computing on cluster mobile devices was carried out in the following way:

- the ensemble random forest algorithm is implemented by software tools of Scikit-Learn library;
- the software tools of Joblib library were used as the basis of the software tools of Scikit-Learn library. They ensured parallelization of calculations on physical cores and their flows of computers due to hyperparameter n_jobs=-1;
- scaling of parallelized calculations on physical cores and their flows of computers of the cluster computer system is realized by means of Dask library software tools;
- the physical level of parallel and distributed calculations is carried out on remote cluster computer system.

Thus, the deployment of software - hardware for parallelized and distributed high-performance computer calculations on remote cluster computer system has the form of software – hardware computer calculation pipeline. Visualization of the typical example of software – hardware computer calculation pipeline is shown in Fig. 5 [14].

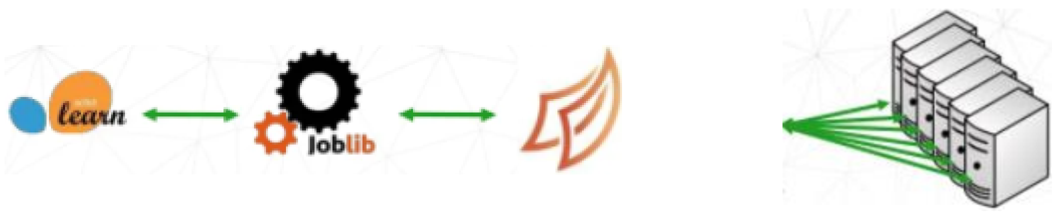

Figure 5. Software – hardware computer calculation pipeline [14]

To minimize the cost of calculation resources (processor time and memory) and maximize the accuracy of the random forest ensemble algorithm, the optimal number of decision trees was found. The optimization is performed due to the comparison of errors on the training and test samples (Fig. 6) during cross-examination, similar to that one where the detection of the beginning of the retraining effect is considered.

Evaluation of the robustness of the practical work for the developed algorithmic support based on artificial intelligence (random forest ensemble algorithm) and software – hardware based on parallel programming using high-performance calculation on cluster computer systems was carried out by calculating the mean square deviation of the error during cross-examination.

Quality metrics: accuracy, roc_auc, and f1 were used for visual interpretation, stability, and complete characteristics of the practical operation accuracy for the developed algorithmic support based on artificial intelligence and software – hardware on the basis of parallel programming using high-performance calculation on cluster mobile devices.

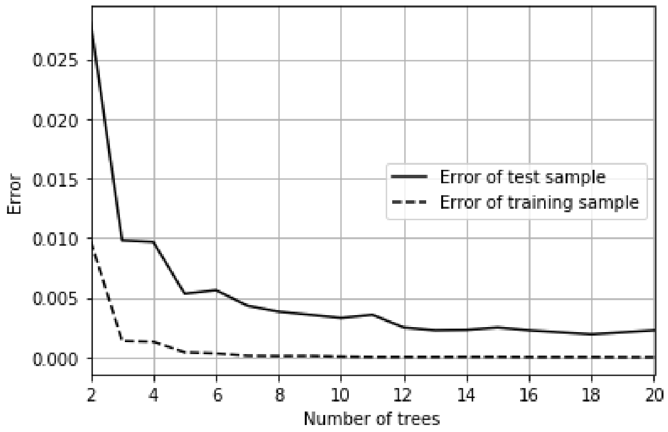

Figure 6. Evaluation of the optimal number of trees in the random forest algorithm

For visual interpretation of the accuracy of practical work characteristic, the accuracy quality metric equal to 99.89% was used. The error matrix of the accuracy quality metric in absolute values within both classes is shown in Fig. 7. The normalized error matrix of the accuracy quality metric in relative values within both classes is shown in Fig. 8.

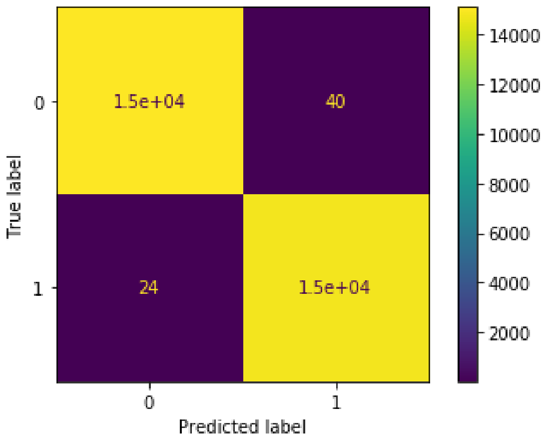

Figure 7. Error matrix, without normalization

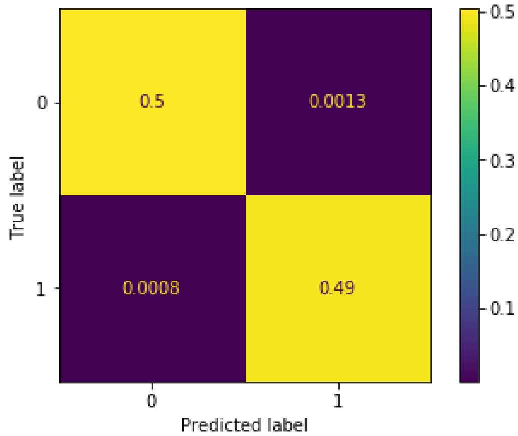

Figure 8. Normalized error matrix

For stable interpretation of the accuracy of practical work characteristic, the quality roc_auc metric equal to 99.89% was used. The roc curve with the area under it equal to 0.9989 is shown in Fig. 9.

For simultaneous characteristic of the practical work accuracy and completeness, we used the quality metric f1, which was 99.89%.

Thus, the next follows from the above mentioned results. Based on EEG signals obtained by experimental measurement of the brain electrical activity during the movement of of the left and right hands thumbs, we obtained input and output data for training the ensemble random forest algorithm, which was implemented by means of the software tools of Scikit-Learn library. Using the software tools of Joblib library, it was possible to parallelize the calculations while training the ensemble random forest algorithm on physical cores and their computer flows by setting the value of n_jobs hyperparameter to -1. Based on the software tools of Dask library, parallel calculation was distributed to the physical cores and their flows of the cluster computer system, which made it possible to organize high-performance calculation for training the ensemble random forest algorithm. As the result, the quality of the created algorithmic, software – hardware calculation pipeline was evaluated based on quality metrics: accuracy, roc_auc, and f1. All this together made it possible to develop practice-oriented algorithmic and software – hardware for the practical implementation of modern neurointerface for brain-computer interaction.

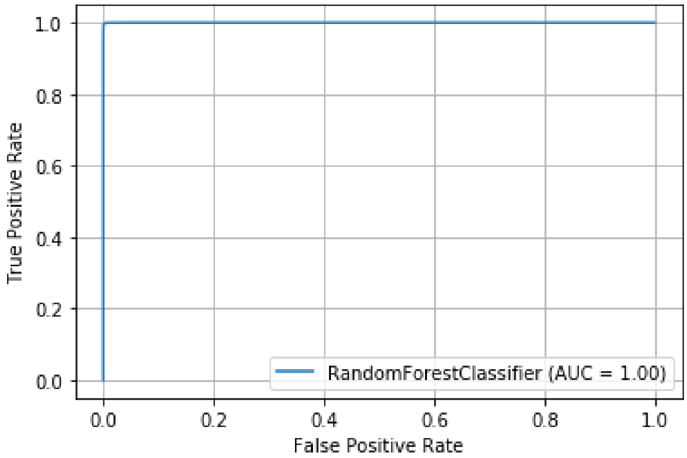

Figure 9. ROC curve

Conclusions. We have developed algorithmic software based on artificial intelligence and software – hardware on the basis of parallel programming using high-performance computer calculation on cluster mobile devices for neurointerfaces of brain-computer interaction, characterized by high values of numerical quality metrics: accuracy=99.89%, roc_auc=99.89%, f1=99.89% on experimental data and high computational efficiency due to parallel and distributed calculations. All this together opens the opportunities for the application of the obtained results in the practical industry.

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УДК 681.3

НЕЙРОІНТЕРФЕЙС ВЗАЄМОДІЇ МОЗОК-КОМП’ЮТЕР НА ОСНОВІ ШТУЧНОГО ІНТЕЛЕКТУ ТА ЙОГО ПАРАЛЕЛЬНОГО ПРОГРАМУВАННЯ З ВИКОРИСТАННЯМ ВИСОКОПРОДУКТИВНИХ КОМП’ЮТЕРНИХ ОБЧИСЛЕНЬ НА КЛАСТЕРНИХ МОБІЛЬНИХ ПРИСТРОЯХ

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Резюме. *Розглянуто програмно-апаратне заберпечення для реалізації взаємодії активності мозку людини з динамічним рухом частини її верхньої кінцівки на основі штучного інтелекту та його паралельного програмування з використанням високопродуктивних комп’ютерних обчислень на кластерних мобільних пристроях.*

Розгортання програмно-апаратного забезпечення розпаралелених та розподілених високопродуктивних комп’ютерних обчислень на віддаленому кластері мобільних пристроїв організовано у вигляді конвеєра програмно-апаратних комп'ютерних обчислень.

За основу алгоритмічного забезпечення в рамках штучного інтелекту вибрано індуктивний підхід (підхід на основі машинного навчання), що використовує логічну парадигму, зокрема, алгоритм із сімейства ансамблевих алгоритмів – випадковий ліс. Оцінено якість роботи даного алгориитму, яка характеризується високими значеннями числових метрик на експериментальних даних та високою обчислювальною ефективністю завдяки паралельним та розподіленим обчисленням. Зокрема, для наочної інтерпретації характеристики точності практичної роботи використано метрику якості accuracy, яка дорівнювала 99,89%; для стійкої інтерпретації характеристики точності практичної роботи використано метрику якості roc_auc, яка дорівнювала 99,89%; для одночасної характеристики точності та повноти практичної роботи використано метрику якості f1, яка дорівнювала 99,89%.

Алгоритм випадковий ліс реалізовано за допомогою програмних інструментів бібліотеки Scikit-Learn. Використовуючи програмні інструменти бібліотеки Joblib, вдалося розпаралелити обчислення при навчанні алгоритму випадковий ліс по фізичних ядрах та їх потоках обчислювального мобільного пристрою, встановивши значення гіперпараметра n_jobs у стан, що дорівнює -1. На основі програмних інструментів бібліотеки Dask виконано розподілення паралельних обчислень на фізичні ядра та їх потоки в кластері мобільних обчислювальних пристроїв, що дало змогу організувати високопродуктивні обчислення для навчання алгоритму випадковий ліс.

Отримані результати можуть бути покладені в основу розроблення високопродуктивного програмно-апаратного забезпечення для ефективної роботи нейроінтерфейсів взаємодії мозок-комп’ютер.

Ключові слова: *нейроінтерфейс взаємодії мозок-комп'ютер; штучний інтелект; паралельне програмування; високопродуктивні комп’ютерні обчислення, кластерні мобільні пристрої.*

https://doi.org/10.33108/visnyk_tntu2023.04.026 *Отримано 09.10.2023*