APPLICATION OF METROLOGY AND PERFORMANCE METRICS IN MEASURING THE PREDICTION OF COGNITIVE STRESS THROUGH MACHINE LEARNING

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ABSTRACT

Machine learning as domain represents integral element, part of artificial intelligence that uses mathematical algorithms to „train“ data and „learn“ machine learning models according to appropriate behavior patterns to result in corresponding output values. The brain-computer interface represents the ability to connect the brain and a machine, i.e., recording and transmitting signals from the brain to the computer and vice versa (in the form of positive or negative feedback), with the aim of controlling a computer or external device or managing one's cognitive abilities. Cognitive stress forecast involves the implementation of machine learning model, recording brain signals, creating the structured database of input values derived from brain-computer interface device (EEG signals either recorded from the brain, artificially generated and/or extracted features from those data inputs). Machine learning model called Support Vector Machine (SVM) and its’ classifier are used for the classification of cognitive stress output predictions based on the available structured database of EEG data. The performance of the SVM model was assessed using formulas to obtain performance metric values such as accuracy, sensitivity, specificity, Matthews correlation coefficient (MCC).

INTRODUCTION

Machine learning is a subgroup, a subfield of the concept of artificial intelligence that uses algorithms, statistical models, and functions making it possible for the machine to „learn“ and „train“ data, with the capacity to forecast, predict future outputs [1]. The brain-computer interface represents the prevailingly logical link between the brain and machine, i.e., recording and transmitting signals from the brain to the computer and vice versa, with the aim of managing a computer or external device [1]. EEG, or electroencephalogram and the input data characteristics obtained from it, represent a non-invasive recording of brain activity, namely the neurological and physiological reactions of a group of neurons in the brain to external or internal stimuli [1]. EEG application potential spans from the medical to the non-medical domain, representing with a certain degree of credibility, metrics of various mental states and internal experiences of patients and/or users.

The goal of this research is to develop accurate prediction models that can provide valuable insights or enable interventions in real-time based on predicted levels of cognitive stress or the likelihood of output values [1] In the implementation of machine learning model, in the forecast of cognitive stress obtained through the brain-computer interface (BCI) or artificially generated EEG data, preprocessing is one of the most important steps for gaining meaningful results. Preprocessing is a key factor for the accuracy and efficiency of the prediction system.

Classification of EEG data is the most significant component of this part of the process, as classification allows the creation of real-time expectation models for each subject [2]. Here we emphasize the importance of EEG data classification, which is central to the development of models that can function in real-time and adapt to individual characteristics. For the purposes of classifying cognitive stress based on EEG data, we used the machine learning technique Support Vector Machine (SVM).

Processing, analysis, management and handling of EEG signals for the purpose of predicting cognitive stress, as well as other mental states and neural activities, is becoming increasingly interesting for researchers, medical academic community, as well as commercial use in the domain of private enterpirses. It is becoming prevailing trend in both scientific and commercial application. The integration of machine learning, as well as artificial intelligence and deep learning, with EEG and brain computer interface technology opens up a world of new possibilities, promising to reconceptualize the way scientists, researchers and ordinary citizens think and imagine the functions of the brain, discovering new possibilities in theory, as well as in practice.

RESEARCH METHODS

Authors’ main motivation are the inquiry and examination of probabilities in potential applications of the Support vector machine model and machine learning methods in general, by investigating the primer of the classification and prediction of cognitive stress using artificially generated EEG signals as input values.

The paper describes the preprocessing procedures, feature extraction techniques, fundamental principles of SVM (Support Vector Machine) model operations, and metrics for signal evaluation and classification. The research tries to determine, in a elaborate and argumented manner, expressing goals, subject of matter, methods (of achieving performance metrics and conclusions), accuracy and efficiency of the SVM model in predicting cognitive stress levels based on artificially generated EEG signals. To evaluate the model's performance, several metrics are used to quantify the model's performance, including accuracy, specificity, and Matthew's Correlation Coefficient (MCC) [1].

Data Collection — The basis of this research is EEG data used for training and testing the SVM model. The Laboratory of Biomedical Engineering and Instrumentation at the Faculty of Technical Sciences, University of Novi Sad provided artificially generated EEG data with labeled cognitive stress levels. The EEG data was provided for the purpose of a master's thesis referenced in Litareture list.

Data Processing — Before placing the EEG data into the structured database and implementing it in a SVM model, several preprocessing steps were applied to enhance the data quality and reduce noise:

Filtering — A pass filter was used to remove unwanted frequency components outside the range of interest (e.g., 0.5-30 Hz) to focus on relevant brain activity [4]. Artifact Reduction — Artifacts such as eye blinks and muscle movements were identified and removed using established techniques such as Independent Component Analysis (ICA) [3], [4].

Model Training — The SVM model represents effective and dynamic supervised learning algorithm and was used to train a predictive model. The previously processed EEG data, along with corresponding labels indicating various levels of cognitive stress, were divided into training and validation sets to prevent overfitting. SVM model hyperparameters, such as kernel type, regularization parameter (C), and gamma, were optimized using techniques like random search to achieve the best performance.

Evaluation Metrics — The performance of the SVM model is assessed using specific classification performance metrics [1]:

Accuracy — The ratio of true positive predictions to the total number of positive predictions, measuring the model's ability to avoid false positive predictions.

Specificity — The ratio of true negative predictions to the total number of actual negative instances, assessing the model's ability to detect negative cases.

Matthews Correlation Coefficient (MCC) — A balanced metric that takes into account true and false positives and negatives, providing a comprehensive evaluation of the model's performance.

The data collection process, preprocessing steps, feature extraction techniques, SVM model training, and evaluation metrics are carefully selected to ensure robust and reliable results [1].

SUPPORT VECTOR MACHINE

The machine learning technique used for this purpose is the Support Vector Machine (SVM) method. This is an example of a specific technique in machine learning that can be used in metrology for classification and prediction, which is relevant for measurement accuracy and efficiency.

Preprocessed EEG data, along with corresponding labels indicating different levels of cognitive stress, were divided into training and validation sets to prevent overfitting [1].

The hyperparameters of the SVM model, such as the type of kernel, regularization parameter (C), and gamma, were optimized using techniques like random search to achieve the best performance[1].

The performance of the SVM model was evaluated using specific relevant classification performance metrics [1]:

1. Accuracy — measures the model's ability to avoid false positive predictions;
2. Sensitivity — true positive rate;
3. Specificity — evaluates the model's ability to detect negative cases;
4. Matthew's correlation coefficient (MCC) — provides a comprehensive assessment of the model's performance.

Perspective on high and low cognitive stress includes the perception of what constitutes high or low cognitive stress and it can vary from person to person, as well as depend on various factors, including individual characteristics, testing experience, and the specificity of the cognitive task at hand.

Cognitive stress is a highly subjective experience, and what one person finds highly stressful, another may not. The same task that causes high cognitive stress as cognitive process of single individual may be routine and stressless experience for another individual.

We chose a stress level threshold of 0.9, which is considered quite low on most stress scales, assuming that higher scores indicate a higher stress level. A score of 0.9 is considered low on most stress scales due to its scaling [1]. The device that assessed cognitive stress was based on a narrow scaling range [1].

Multiple aspects of the problem were considered to arrive at an optimal threshold. Threshold optimization remains a challenging problem. In some other contexts, for example, in clinical or research settings, a score of 0.9 might indicate a alarming level of cognitive stress requiring attention, action or even a medical intervention [1].

The Laboratory for Biomedical Engineering and Instrumentation at the Faculty of Technical Sciences, University of Novi Sad provided a database of artificially generated EEG signals used in this research [1].

EXPLORING SVM CLASSIFIER FOR COGNITIVE STRESS CLASSIFICATION

The possibilities of SVM model for classifying binary options, i.e. two levels of cognitive stress, using input values in a form of artificially generated signals database, were investigated using the free Matlab programming language software called Matlab Online. One of the biggest advantages, and at the same time disadvantages of the SVM model, is that it is reliable in predicting outputs using small input data sets, but at the same time it is not suitable for processing large amounts of data. Also, SVM only supports binary classification problems.

The first step at the beginning of coding for creating plausible machine learning model is data type conversion. It is required at the beginning of the programing code. In our research it is necessary to perform reading from .xlsx to .mat extension, in the sense of converting string values to numerical values represented in the Matlab software .mat extension. This is a significant prerequisite, along with properly trained data, for efficient and functional programing code, as well as valid and accurate output prediction results.

In feature extraction process, which is also necessary for more valid and accurate prediction results, the following features of artificially generated EEG signals database were selected as the most effective: mean feature method, spectral feature extraction method, centroid feature method, as well as Higuchi Fractal Dimension (HFD) method. The highest to the lowest impact on the final result performance metrics was recorded with the presence of features in aforementioned order.

In the next part of the paper we will analyze the contributions of every single implemented extracted feature of EEG signals database in our development and programming of Support vector machine learning model:

Mean feature – This feature extraction method involves calculating the average value of all data points in the signal. It provides us with information about the central tendency of the signal values, i.e., the direction of movement of the signal values. It also helps in understanding the behavior of the signal over time or frequency, in other words, how the mean value signal is distributed.

Spectral feature extraction method – This group of methods includes the analysis of different frequency bands in the signal, such as alpha, beta, gamma, delta, and theta bands.

Centroid feature – This method is used to determine the point that represents the center of mass of a set of data points in the signal. It gives us the position, location of the centroid in the dataset.

Higuchi Fractal Dimension (HFD) method – This method estimates the complexity of the signal based on its fractal dimension (irregular shapes). It is used to determine how much the signal has irregular, i.e., fractal shapes and can be useful in analyzing signals that have different degrees of complexity.

The highest peak in accuracy of the SVM model prediction performance metrics was obtained by introducing the mean feature. The next highest percentage increase, which were considered after the previous one, were spectral feature extraction method, as well as the centroid feature method. Considerably small percentage peak in performance metrics of SVM model prediction, especially concerning accuracy, was obtained by implementing and using the Higuchi Fractal Dimension (HFD) method.

PERFORMANCE METRICS

Formulas were used to obtain values of performance metrics such as: accuracy, sensitivity (true positive rate), specificity (true negative rate), Matthews Correlation Coefficient (MCC). Terms TP, FP, TN, and FN represent true/false predictions for positive/negative labels, which are used to describe different outcomes of classification techniques [5]. Accuracy is the most commonly used metric to determine the classification capacity to distinguish between classes, and is calculated using the equation [5]:

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN)$$

Sensitivity measures the ratio between the number of accurately classified, predicted positive EEG classes, segments (true positive instances) and the total number of true positive EEG segments, instances available in the dataset) [6].

Sensitivity = TP/(TP+FN)

Specificity (true negative rate) measures the proportion, the number of true negative instances, cases (correctly predicted negative class) divided by the total number of true negative instances [6]. In short, specificity tells about the ratio between predicted negative observations and the total true negative observations [6].

Specificity = TN/(TN+FP)

The performance of the SVM model can be analyzed using an additional parameter called the Matthews Correlation Coefficient (MCC). The Matthews Correlation Coefficient (MCC) is a balanced metric that considers true and false positives and negatives, providing a better measure of assessment for unbalanced datasets [7].

$$MCC = (TP \times TN - FP \times FN) / \sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}$$

MCC ranges from -1 to +1, where +1 indicates perfect prediction, 0 is random prediction, and -1 indicates complete disagreement between prediction and original instances [7]. When evaluating classifiers, a higher MCC value indicates better overall performance [7]. The MCC parameter is defined in a way that provides a more balanced measure of classification performance considering sensitivity, specificity, and accuracy results together [7].

Table 1 Performances of the model for detection of cognitive stress depending on inputs

	Accuracy	**Sensitivity**	**Specificity**	**Matthews Correlation Coefficient**
Performance metrics with input values (IV)	**62.857 %**	**26.923 %**	**98.113 %**	**0.35772**
Performance metrics with IV and extracted features	**75. 333 %**	**38.462%**	**93.939 %**	**0.40666**

CONCLUSION

The obtained results present the potential and capacity of the SVM model to make a successful classification between two levels of cognitive stress – high and low. The maximally achieved performance metrics using SVM model of machine learning were: average accuracy of 75.33% and a specificity of 93.94% [1]. Significant improvement has been made using the set of appropriate EEG data features as input signals and implementing them in the developed model. The main limitation of this study is the small data set available to us. SVM model is founded on the binary classification concept. This concept shows that SVM is a good choice for the classification process and presenting prediction output values, given the small data set is available in the obtained database of the artificially generated EEG signals. This is important fact primarily for easier understanding of the results by users and implementing possible feedback mechanisms. The research results, after additional research and testing, can be applied in medical, but also in non-medical fields. The research, potentially offers application in the diagnosis and therapy of attention disorders, focus, hyperactivity, in cases of autism, depression, etc. The research results can be used to possibly improve learning, manage stress especially in the workplace, analyze, detect and even treat anxiety disorders, as well as in other various situations and environments, of the medical or non-medical domain. In virtual environments and/or video games the research allows detecting, reading and predicting the cognitive stress as users' brain parameter, at the same time contributing to a greater user experience and highly realistic environment in virtual reality and/or video games.

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