A Novel Machine Learning Approach to Working Memory Evaluation Using Resting-State EEG Data

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Abstract

The human working memory and its cognitive functionality are essential for a range of fundamental to complex processes throughout our entire life. Damage and abnormalities can cause severe effects on an individual's life. Predictive healthcare analytics can support and accelerate the diagnosis of such effects in the early stages. Using resting-state EEG data and the results of a cognitive test-battery for attentional performance, we developed a machine learning approach to evaluate the human working memory and detect hyper- or hypoactivation. By predicting the test-battery results using the EEG recording of a patient, we enable a fast, objective, and accurate evaluation. Furthermore, we identified the most relevant brain regions (prefrontal cortex and dorsolateral prefrontal cortex) and the corresponding frequency sub-bands (9.5-11.5 Hz and 11-13 Hz). With a balanced accuracy of 87.50%, our results set a new benchmark in evaluating the working memory using only resting-state EEG recordings.

Keywords: E-Health, working memory, cognitive performance, electroencephalography, machine learning

Introduction

According to the American Centers for Disease Control and Prevention, more than 16 million people suffered from cognitive impairment in 2010 in the US alone. With an aging society, the global case numbers are expected to rise. Cognitive functionality and attentional performance are among the key mental properties in

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our daily lives, and a decline can have tremendous effects. These cognitive abilities are mainly processed and located in the human working memory, representing the third and last memory category next to short- and long-term memory (Chai et al. 2018). The selection of information from working memory and attention to sensory stimuli represent the basis for shared neural mechanisms (Panichello and Buschman 2021). Many small tasks (e.g., counting change or even negotiating in daily traffic) are essentially processed in the working memory. Most importantly, working memory plays a key role in an individual's academic and professional success, as well as in a set of life-critical situations (e.g., traffic control or military operations). Our working memory is one of the central brain structures, which starts to develop in early childhood, and is mainly located in the prefrontal cortex (PFC), enabling us to process and temporally store task-relevant information and is, therefore, crucial to keep things in mind while performing complex tasks (Rohlf et al. 2011). Therefore, the working memory represents a central cognitive function and is assumed to operate whenever information has to be retained and manipulated over brief periods to guide an immediate response (Linden 2007).

The human working memory can be split into two central systems, the phonological loop for verbal and the visuospatial sketchpad for visual information (Linden 2007), which are supplemented over time by the central executive that involves the attentional control system and the episodic buffer (Baddeley 2000). Although the human brain and its cognitive functionalities have a dominant role in the scientific field of neuropsychological research, there are different approaches and opinions on the exact mechanisms and the corresponding brain regions. However, most classical working memory tasks almost certainly require some degree of prefrontal support, making it the most relevant region for scientific considerations (Curtis and D'Esposito 2003; Linden 2007). Any structural or chemical abnormality affecting the working memory's relevant brain regions can have serious impacts on cognitive performance and the affected person's daily life. Chai et al. (2018) point out various reasons that can cause abnormalities and damage to the working memory. In addition, natural processes like aging can have major effects on working memory and its performance, which can also be amplified by emotions, caffeine, and hormones. Furthermore, young individuals can have similar impairments caused by various mental, developmental, and neurological abnormalities. As a general observation, unusual neural activity, either hyper- or hypoactivation, can be identified in individuals suffering from corresponding effects (Chai et al. 2018).

Attention-Deficit Hyperactivity Disorder (ADHD), for instance, represents a significant cognitive disease the roots of which are mainly based on working memory. ADHD refers to a variable cluster of hyperactivity, impulsivity, and inattention symptoms, which substantially affects the individual's normal cognitive and behavioral functioning. Children and adolescents who have ADHD are at risk of later delinquency problems, and some symptoms may persist through the lifespan (Barry et al. 2003; Binhadyan et al. 2014). ADHD is one of the most common neuropsychiatric disorders in childhood, with prevalence rates estimated at 5–10% and 4% of adults (Biederman 2005). Such damage and abnormalities are mainly determined using Electroencephalography (EEG), which enables insights into working memory activity during different states and tasks. The resulting data is rich in information, which can be extracted using different techniques (Lenartowicz and Loo 2014).

In this study, considering the described topics and details, we deal with the following research question: Is a machine learning (ML)-based algorithm able to accurately evaluate the working memory of an individual by automatically analyzing resting-state EEG data?

As a result of this procedure, our ML algorithm was capable of distinguishing between the two intervention groups with a balanced accuracy of 87.50%. Our key findings therefore include the following:

1. We develop a high-performance algorithm to evaluate the working memory, exclusively using resting-state EEG recordings with a balanced accuracy of 87.50%, setting a new benchmark.
2. The high accuracy of the ML model enables the precise evaluation of the working memory and detection of early symptoms without the need for further testing, exclusively using the resting-state EEG data of an individual.
3. By identifying the most predictive frequency sub-bands (9.5-11.5 Hz and 11-13 Hz) and brain regions (prefrontal cortex and dorsolateral prefrontal cortex) to differentiate a healthy from an abnormal working memory, we extend the work from Ghosh et al. (2015), which focused on a broader frequency range,

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and present the detection of highly relevant cognitive diseases related to working memory as a further use case.

4. Our ML model contributes to IS research in healthcare, as it represents an accurate, fast, and cost-efficient predictive healthcare approach for the early diagnosis of working memory abnormalities based on resting-state EEG recordings (Kohli and Tan 2016).

The paper is organized as follows: First, we present an overview of the research background on the test for attentional performance, relationships between working memory and electroencephalography, as well as related studies. Subsequently, we describe the methodology, including our data preprocessing, ML model, and the dataset used for evaluation. After that, we show the performance results of our implemented method. We then discuss the results before concluding with limitations and offering suggestions for future work.

Research Background

Test for Attentional Performance

The Test for Attentional Performance, developed by Zimmermann and Fimm (2012), was initially used for the assessment of attentional deficits in patients with cerebral lesions. The core of the procedure are reaction time tasks of low complexity allowing the evaluation and identification of particular deficiencies. The tasks consist of simple and easily distinguishable stimuli that the patients react to by a simple motor response, with the aim of measuring and evaluating the working memory (Leclercq and Zimmermann 2002). Today, the test battery is suitable for the analysis of a wide variety of actions that are not based on overlearned routines (Leclercq and Zimmermann 2002) and is therefore highly suitable for many cognitive impairments, whereas the clinical utility of the test still shows potential use cases (Catale et al. 2009). Catale et al. (2009) used the computerized Test for Attentional Performance to analyze the attentional and executive functioning of children with mild traumatic brain injuries, focusing on their probands working memory (Catale et al. 2009). Zimmermann and Fimm (2012) describe the concept of attention as the summary of actions that are not based on overlearned routines. Their hypothesis that every conceivable or non-automatic practical action is under control of the attentional system underlines the importance of the research and the need for deeper insights regarding this particular topic. For the test at hand, probands are shown a series of numbers on a screen while being asked to press a button as fast as possible when the number on the screen is equal to the second last number shown. During this procedure, which requires continuous control of the information flow, besides the number of correct, wrong, and missed matches, the mean reaction time for correct answers and the corresponding standard deviations are measured. In simple terms, a faster reaction time for a correct answer suggests a better working memory, allowing an accurate evaluation of the cognitive performance. In the clinical context, the Test for Attentional Performance is used for a variety of cognitive abnormalities and diseases like ADHD, Dementia (Alzheimer), Schizophrenia, Sleeping disorders, and stress-caused cognitive impairments (Leclercq and Zimmermann 2002).

Working Memory and Electroencephalography

Human brain analysis is an extensive and heterogeneous scientific area, with intensive research in various complex topics. High-functional technologies (e.g., Magnetic Resonance Imaging (MRI) and EEG) have enabled the scientific world to gain a deeper understanding of the (human) brain, its functionalities, and occurring misfunctions. EEG signals of human brain activity were, in particular, confirmed as a key method for the real-time, objective determination of cognitive load level - in the case of working memory, in the frontal EEG channels (Zarjam et al. 2010). The high data granularity allows an ML-based algorithm to detect and compare patterns with the aim of identifying abnormalities. Zarjam et al. pointed out the high feasibility and efficiency of EEG to record the activity along the human scalp in cognitive science and conducted a study using the frontal channels (frontal brain regions) to measure the cognitive load in the working memory of their probands (Zarjam et al. 2010). In a later study, Zarjam et al. (2011) characterized the working memory load of five subjects using an ML-based classification on EEG delta activity during cognitive tasks, achieving up to 100% accuracy, showing that the classification of the working memory based on EEG recordings is feasible, even though on a smaller scale. EEG also plays a key role in diagnosing many working memory-

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related diseases, like, for instance, ADHD. Here, the slow *theta*-waves (4-7 Hz) and/or fast *beta*-waves (14-30 Hz) were identified as biomarkers for a potential diagnosis (Lenartowicz and Loo 2014). In their EEG study on working memory, Ghosh et al. use a frequency range of 8 to 30 Hz, focusing on the *alpha* (7.5-12.5 Hz) - and *beta* (12.5-30 Hz) waves, following Davis et al. (2010), claiming these frequency bands to be the most relevant and active while performing tasks involving memorization and recognition (Ghosh et al. 2015). Another study conducted by Onton et al. (2005) defined the frontal midline *theta* waves (5-7 Hz) as relevant for working memory analysis using EEG and more precisely identified higher *beta*-activity (12-15 Hz) on the Fz-electrode during memory tasks. Besides the EEG data and the relevant frequency sub-bands, another important consideration are the relevant brain regions for the working memory, which play a key role in a precise diagnosis. Among many works, a study conducted by Curtis and D'Esposito on monkeys identified a persistent activity in the PFC during working memory tasks, supported by the dorsolateral prefrontal cortex (DLPFC) (Curtis and D'Esposito 2003).

Further studies and scientific approaches conclude that the PFC and especially the DLPFC are crucial in working memory and episodic memory processes (Balconi 2013; Lenartowicz and Loo 2014), with the DLPFC being highly relevant for tasks demanding executive control, manipulation, and information updating (Chai et al. 2018). Above all, the exact role of the DLPFC and its importance for the working memory still seems to be partly unknown (Barbey et al. 2013). Based on the EEG recordings and the above-mentioned filtering of the relevant data for the working memory activity, it is possible to train an ML-model for fast and accurate signal processing for working memory evaluation. Comparable to Zarjam et al. (2011), Zhang et al. (2020) very recently developed a standard linear regression model, using relevant features from eight frontal electrodes, to predict working memory abilities from EEG signals. They claim the model to be the first of its kind and conclude that the predictive relationship between working memory and frontal brain activity through EEG is feasible and accurate (Zhang et al. 2020). Furthermore, Ieracitano et al. (2019) were able to classify brain states using resting-state EEG and different ML models, with a high accuracy of 95.76% (Ieracitano et al. 2019). Table 1 provides a representative overview of these studies.

Table 1. Current Approaches for Working Memory Evaluation Using EEG Data

Investigation	Data	Method	Performance	Reference
Distinction between three working memory load levels	EEG recordings during a reading task of 5 subjects	Support Vector Machine	Accuracy: 100%	(Zarjam et al. 2011)
Distinction between Alzheimer's disease probands and healthy probands	Resting-state EEG recordings of 189 subjects	Multilayer Perceptron	Accuracy: 95.76%	(Ieracitano et al. 2019)
Prediction of working memory based on the N-back task score	Resting-state EEG recordings of 142 subjects	Multiple functional linear model	R^2: 72%	(Zhang et al. 2020)

However, so far, no ML approach allows an objective distinction between probands with low-performing and high-performing working memories with a high level of accuracy, using resting-state EEG data alone, which are less complex to record, eliminating the need for extensive and error-prone tests.

Methodology

The methodology follows the Design Science Research Approach by Hevner et al. (2004). Thereby, we develop an algorithm to classify EEG data using a fine-graded 33-point spectrum (Buettner et al. 2019), based on selections regarding the frequencies and channels, to predict and evaluate the working memory abilities of individuals.

Novel Machine Learning Approach

The evaluation algorithm was built based on a novel ML approach, which has already been applied with great success to similar cognitive diseases (Buettner et al. 2020). The implemented approach is based on the unfolded EEG spectra using the Fast Fourier Transform (FFT) and a Random Forest (RF) Classifier as an ML algorithm. The novel ML approach is based on the hypothesis that the division of a frequency range from 0.5-50 Hz into a fine-graded equidistant spectrum provides a higher level of information content and quality (Buettner et al. 2019). The ML model at hand was developed with an adapted frequency range of 0.5-30 Hz, overlapping frequency-buckets to map every possible frequency area and give the ML model the opportunity to be more flexible regarding the feature selection, and furthermore, a 2-step process to identify the best performing features in terms of the prediction accuracy, as well as the optimal parameters for the estimator (hyperparameter tuning). By doing so, the model was optimized in a 2-step iterative process, first to identify the most predictive features and parameters and second, evaluate the model on the unseen test data. Five models were trained and optimized in parallel to find the most suitable classification ML-model, as shown in Figure 1. All computations were done in Python 3.7.

Figure 1 presents the procedure for identifying the critical frequency sub-bands for the working memory evaluation using the first model and developing the final model based on these findings, iteratively optimizing through a selection of the relevant electrodes (working memory) and methodologically optimizing the RF classifier. All of the models started with the identical 33 features and underwent the same methodical process of a feature- and hyperparameter selection. In the end, the final and most predictive features were used to evaluate the model.

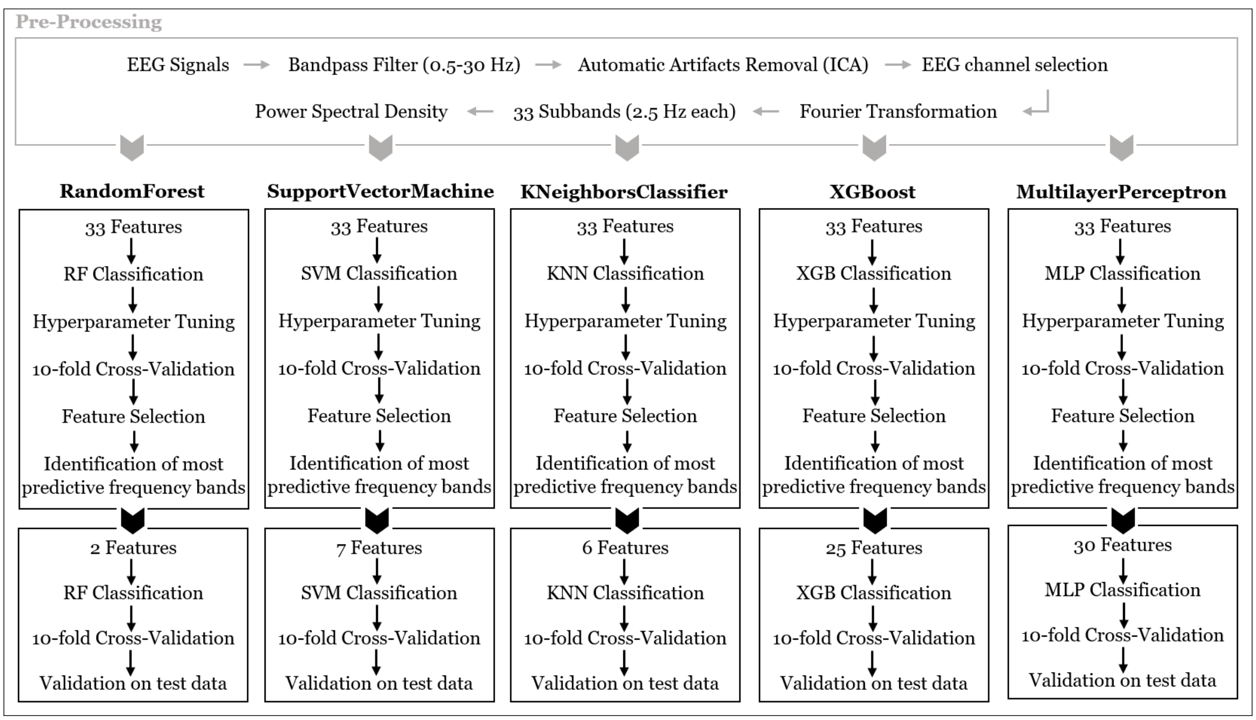

Figure 1. Methodology Based on the Two-Model Machine Learning Approach

Data Preprocessing and Machine Learning Model

Based on the corresponding literature and findings of the first model, the frequency bands relevant for working memory activity were adapted. Therefore, only the frequencies of the alpha (7.5-12.5 Hz)-, theta (3.5-7.5 Hz)- and beta-bands (12.5-30 Hz) were considered in the first model to guarantee a reliable model for the use case. We implemented a bandpass filter using the digital finite-impulse-response filtering, keeping a

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low frequency of 0.5 Hz (high-pass) and a high frequency of 30 Hz (low-pass). Furthermore, the frequency buckets were overlapped in a small range to increase the precision and give the algorithm more flexibility in the feature selection. To remove potential artifacts (i.e., eye blinks and movements, muscle activities, or general electrode noises) from the resting-state EEG data, we used the independent component analysis by implementing the Information-Maximization approach to transform the EEG signals into statistically independent components (Bell and Sejnowski 1995). The number of components was set to 7 and the maximal iteration to 800 while using the fastica method. To only include the brain regions relevant for working memory activities (PFC and DLPFC), following Balconi (2013) and Lenartowicz and Loo (2014), we identified the corresponding electrodes according to Chai et al. (2018). Figure 2 displays the different brain regions covered. Hence, we selected the channels Fp1, Fpz, Fp2 (PFC), and F3, F4 (DLPFC), marked in red and light purple.

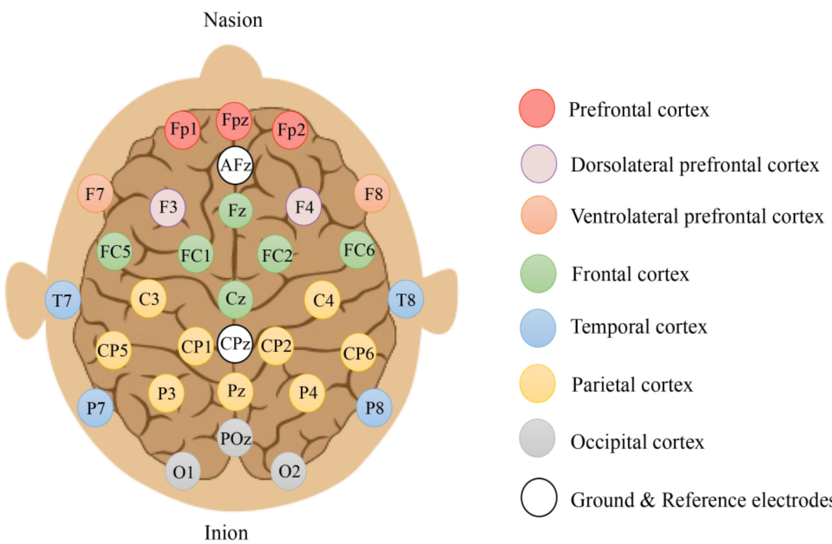

Figure 2. Brain Regions and Corresponding EEG Electrodes (Chai et al. 2018)

We also extended the work of Zhang et al. (2020), who selected relevant EEG electrodes for working memory abilities, to train a regression algorithm - using EEG recordings of working memory tasks, contrary to our approach of using resting-state EEG data only. Afterward, we implemented an FFT approach to perform a spectral analysis of the EEG signals. The FFT calculates the power spectrum, which allows an interpretation of the EEG signals (Welch 1967). To receive the highest information content, we set the bandwidth to 2.5 Hz (overlapping buckets), which resulted in the desired fine-graded 33-point spectrum, applying and adapting the novel approach of Buettner et al. (2019), which resulted in a fine-graded 88-point spectrum. Inter alia, the combination of the fine-grained EEG spectra and the RF algorithm showed very good results in diagnosing internet addiction (Gross et al. 2020), epilepsy (Buettner et al. 2019), and excessive daytime sleepiness (Breitenbach et al. 2020) under the use of the same methodology.

The RF Classifier is a popular ML model that operates by training a given amount of independent decision trees and therefore is highly suitable for larger datasets. Giving a variety of opportunities for feature selection and hyperparameter tuning, the RF can be optimized to attain a high and robust prediction accuracy (Breiman 2001). Therefore, the selected, most important variables (features) are based on the statistical significance of the corresponding feature on the RF model (Strobl et al. 2007). A diversity of further ML models *(K Nearest Neighbor Classifier (KNN), XGBoost (XGB), and Multilayer Perceptron (MLP)* were trained to determine the one that was most suitable, and best performing.

Evaluation and Validation Procedure

To increase the reliability and stability of the models, a k-fold cross-validation was performed. In doing so, the dataset was split randomly with every iteration in different train- and test-splits. Therefore, the outcome of every iteration is unequal. The k-fold cross-validation divides the dataset into k-folds and learns a classifier with (k-1) folds. An error value is calculated by testing the classifier with the remaining fold. As a result, the confusion matrix of the model shows which subjects the classifier either classified as true or false (Kim 2009). For the model at hand, the 10-fold cross-validation with 10 hold-out validation cycles, the performance and accuracy of the trained model were validated using the test-split, containing the data of 17 - to the algorithm unknown - probands. Using this validation methodology, we can ensure the robustness and reliability of the model performance for the identified use case (Gross et al. 2021b).

Dataset, Acquisition and Evaluation Premises

To develop, train, and evaluate the above described ML approach, the data from the "Leipzig Study for Mind-Body-Emotion Interactions" (LEMON) was used. The underlying study includes initial data of 227 healthy participants, subdivided into two groups of age (young: 20-35 years of age and older: 59-77 years of age) differing in gender and level of education. All participants were tested at the Day Clinic for Cognitive Neurology of the University Clinic Leipzig and the Max Planck Institute for Human and Cognitive and Brain Sciences between 2013 and 2015 in Leipzig, Germany. Next to the resting-state EEG data of the probands, further recordings of mind-brain-body-related data are included in the dataset (Babayan et al. 2019). The EEG data were recorded with a sampling rate of 2,500 Hz and afterward downsampled to 250 Hz for further processing, using a 62-channel (61 scalp electrodes and 1 VEOG electrode – all referenced to the FCz electrode) EEG, according to the international standard 10-20 (10-10) extended localization system. Each participant's EEG record lasts 16 minutes, consisting of separate blocks (60 seconds each) (Babayan et al. 2019).

Regarding the aim of developing an ML approach for working memory evaluation, the included Test of Attentional Performance with its subtest working memory, was deployed. This test was administered electronically via computer and is based on the test setup developed by Zimmermann and Fimm (2012), described in the research background. The procedure measures the reaction time (mean) needed to give a correct answer on a simple working memory task. Before preprocessing the data with the FFT and EEG spectrum, those participants with discrepancies (protocolled by the moderator) were excluded from the dataset to avoid distortion. Of these remaining 214 probands, two classes were derived. Therefore, caused by the imbalance of the data and different risks of miss-classifications or miss-measurement, the 39 individuals with the highest (slowest) mean reaction time and the 39 individuals with the lowest (fastest) were converted into a sub-dataset. The usage of quantiles makes sense in this context because probands near to the mean value are ignored, and the model performs better on the identification/classification for high- or low-performing (hypo-/hyperactivated) working memories. Further on, the group labeled with the slow reaction time (low-performing) can be labeled as the individuals with a bad or somehow damaged working memory and potential symptomatic for cognitive decline. On the other hand, the probands with an above-average reaction time (high-performing) may suffer from hyperactivity in their frontal brain regions. The mean value of a correct answer for all participants included in the overall dataset (214 probands) is 578.40 ms. Based on the split into 80% training data and 20% unseen testing data, the ML algorithm was trained with the data of 62 participants and evaluated with completely unseen data of 16 participants (Gross et al. 2021a).

Results

Overall Performance of the Classifier

Our final RF classifier, trained with the most predictive EEG sub-bands (9.5-11.5 Hz and 11-13 Hz) - representing the high *alpha* - and low *beta*-bands, achieves a reliable and balanced accuracy of 87.50%. Different approaches of hyperparameter tuning were conducted to optimize the model's performance concluding in the number of trees to grow of 10 and the maximal depth of each tree to be 9.0, using the entropy as the criterion for the information gain. Other trained models (see Figure 1) performed very differently: classical algorithms like KNN were also able to reach high levels of accuracy, whereas newer algorithms like the XGB algorithm did not seem to be suitable for the task and data at hand. Furthermore, basic neural networks (i.e., MLP) were tested. All the mentioned models were trained with a data split, using 80% of the data for training and the remaining 20% as the testing data to be predicted on. Below, Table 2 displays the results and

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evaluation metrics of the trained and optimized model (RF), whereas Table 3 represents the corresponding confusion matrix. The stated values are based on unseen data of 16 probands. As shown in the confusion matrix, of the test-set including data of 16 unknown probands, the final model assigns eight probands (50%) with a high-functional working memory correctly as well as six probands (37.5%) with a low-functional working memory. Respectively, eight probands show above-average working memory activation, and six react below-average. These insights can indicate hyper- or hypoactivity of the individual's brain and reveal potential (early) symptoms or deficits. It should be emphasized that none of the probands have known cognitive or mental diseases or impairments. Nonetheless, the classifier detects structural differences and assigns the two intervention groups with excellent accuracy.

Table 2. Mean Values of Key Performance Indicators Based on Unseen Testing Data

	Machine Learning Algorithms			
Performance Indicator	**RF**	KNN	XGB	MLP
Balanced Accuracy	**87.50%**	81.25%	56.25%	31.25%
Sensitivity (True Positive Rate)	**88.89%**	87.50%	60.00%	n.a.
Specificity (True Negative Rate)	**85.71%**	75.00%	50.00%	35.71%
Positive Predictive Value	**88.89%**	88.89%	66.67%	0.00%
Negative Predictive Value	**85.71%**	85.71%	42.86%	71.43%
Kappa	**74.60%**	62.50%	9.70%	n.a.
F1-Score	**88.89%**	82.35%	63.16%	n.a.

Table 3. Confusion Matrix: Mean Values of all RF Model Cycles Based on Unseen Testing Data

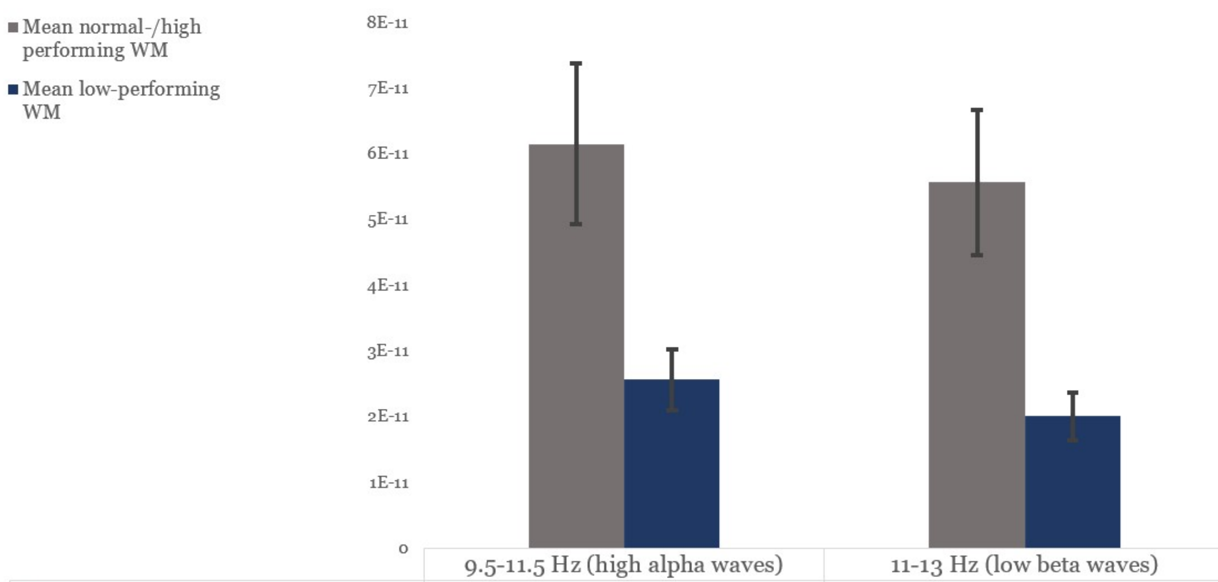
		Reference Values	
		Low-Performer	High-Performer
Predicted Values	Low-Performer	**50.00%**	6.25%
	High-Performer	6.25%	**37.5%**

Identified Feature Subsets

With our novel ML approach, we extended the standard EEG bandwidths (Delta 1-4 Hz, Theta 4-8 Hz, Alpha 8-13 Hz, Beta 13-25 Hz, and Gamma 25-200 Hz) into a fine-graded 33-point spectrum, referring to the fine-graded 88-point spectrum (Müller-Putz et al. 2015), under the use of partially overlapping frequency sub-bands. Through our 2-step approach, we identified and selected the most relevant electrodes for working memory activation during specific tasks (Fp1, Fpz, Fp2 (PFC) and F3, F4 (DLPFC)), which we averaged over the defined frequencies. Due to the overlapping of frequency buckets, we increased the number of features and made it possible for the ML model to identify the most valuable and predictable ones. Resulting from this procedure, we generated our subset of 33 features (33 frequency sub-bands with overlapping 2.5 Hz each) for the final classification model. Using different approaches for variable importance and feature selection of the RF algorithm, we identified the high *alpha* and low *beta* range, to contain the most predictive frequencies: 9.5-11.5 Hz *alpha* and 11-13 Hz *beta*. These very specific frequency sub-bands ensure the reliability and high performance of the model evaluating the working memory.

Discussion

Our model can predict high- and low-performing working memories with a high level of accuracy through our novel ML approach, including feature selection and hyperparameter optimization. Besides the frequency bands (mainly *alpha*-, *beta*- and *theta*- waves for the working memory), the EEG electrodes and corresponding brain regions are crucial for an evaluation of the working memory and the diagnosis of abnormalities or even early symptoms of hyper- or hypoactivation. The importance of the DLPFC for working memory tasks is becoming increasingly clear (Barbey et al. 2013; Chai et al. 2019), while it is also necessary to consider further brain regions (e.g., Parietal Cortex) that are possible locations for working memory activity or abnormalities (see Figure 2). The relevance of the *alpha*-, *beta*- and *theta*- frequencies was confirmed for the activity-analysis in the human working memory. After selecting the most important EEG channels for working memory activity (Fp1, Fpz, Fp2, F3, F4), the most predictive frequency sub-bands were identified (9.5-11.5 Hz and 11-13 Hz), using exclusively resting-state EEG data of the probands. Based on these precise selections, various cognitive and psychological abnormalities can be covered (e.g., Alzheimer's, Schizophrenia, and ADHD), as indicated in previously presented literature. The possibility and feasibility of working memory evaluation using resting-state EEG recordings can reduce the necessity for more or less extensive cognitive test batteries - also considering the susceptibility to errors of such procedures. To further analyze and identify the main differences and characteristics of the two selected frequency sub-bands between high- and low-performing working memories, a one-sided t-test was performed. Based on the alternative hypothesis, that probands with a dysfunctional working memory show a reduced spectral power in the considered frequencies (*alpha-/beta* frequencies) compared to probands with a normal- or high-functional working memory (Sullivan and Feinn 2012). Figure 3 displays the main characteristics of the two classification groups. Based on the differences in the mean values between the two intervention groups, the low-performing memories show a reduced spectral power in both considered frequency sub-bands. This finding implies that our novel ML approach successfully determines and implements a non-linear relation between low- and normal/high - functional working memories. As part of this approach, we averaged the most relevant electrodes over each frequency band, which results in the best classifier performance. Therefore, concerning the evaluation of working memory abnormalities using EEG data, the effects on the fine-graded EEG spectrum are of high relevance.



	9.5-11.5 Hz (high alpha waves)	11-13 Hz (low beta waves)
Mean normal-/high performing WM	6.15E-11	5.56E-11
Mean low-performing WM	2.56E-11	2.00E-11

Figure 3. Spectral Power and Characteristics of the Two Frequency Sub-Bands

Conclusion

Our developed model represents a highly effective working memory evaluation algorithm, which achieves an excellent classification performance based on a fine-graded overlapping 33-point spectrum. The novel ML approach we implemented to develop our model can establish a connection between subjective self-assessments (working memory performance) and objective measurements of brain activity (EEG) with an

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overall accuracy of 87.50%. At this point, our work is the first to propose a method that can differentiate low-performing from high-performing working memories - with such a high degree of accuracy - based on resting-state EEG recordings. Furthermore, our algorithm works fast, accurately, and is cost-efficient, substantially contributing to IS research in healthcare (Kohli and Tan 2016). We affirmed that working memory plays a key role in the human brain, while damage to or abnormalities of the working memory can have tremendous effects. We revealed that the PFC and the DLPFC combined with the high *alpha*- and low *beta* - waves were the most significant, from the scientific as well as the IS point of view. The developed model can bring further insights into a wide variety of cognitive diseases and symptoms caused by working memory hypo- or hyperactivation.

Limitations

While the internal validation is very high due to the hold-out cross-validation, our work's main limitation is based on the absence of external validation and the *LEMON* dataset used to train, develop and test our working memory evaluation algorithm. The data also solely included healthy individuals, and the number of probands (214 after data cleaning) was relatively small, possibly affecting the classification results of the different algorithms tested. Data of patients with specific impairments or diseases could expand the abilities of the model. Furthermore, the age of the participants was unknown and therefore could not be taken into consideration. The EEG data and hence the ML classifier are also affected by other factors such as personality or medication (Buettner 2016). Nevertheless, by comparing the resting-state EEG data with the results of working memory tasks (Test for Attentional Performance), we were able to predict and classify the working memory abilities to a good degree of accuracy.

Future Work

To further advance the robustness and performance of our working memory evaluation, a major basis of our future work is to re-evaluate the algorithm using a larger dataset, which ideally contains probands who suffer from working memory decline and impairments as well as EEG signals with other abnormalities that naturally occur. For this purpose, the selected brain areas (PFC and DLPFC) are highly suitable (Chai et al. 2019). In particular, the DLPFC showed less working memory load-related activation in patients with social anxiety disorder (Balderston et al. 2017). The model with its selected brain regions and frequency bands, therefore, will be tested on a variety of potential cognitive diseases, from ADHD, epilepsy, and schizophrenia to depressive, sleep, and social disorders, as well as certain addictions (e.g., caffeine, alcohol) (Chai et al. 2019). Data, including patients with such cognitive diseases, could give the model the ability to diagnose these and detect early symptoms. Traumatic impairments and injuries related to working memory, which showed similar characteristics (Catale et al. 2009), will also be investigated. Moreover, we will evaluate other feature selection algorithms for identifying predictive frequency bands and further analyze the causes for misclassifications (Chandrashekar and Sahin 2014). For implementation into real-world medical environments, we will also evaluate trust and the acceptance of the approach as well as the influence on the mental workload of medical personnel supported by the system, using different physiological sensors (Gaertner et al. 2021; Rieg et al. 2020; Sauter et al. 2021).

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