Subject-Independent Detection of Yes/No Decisions Using EEG Recordings During Motor Imagery Tasks: A Novel Machine-Learning Approach with Fine-Graded EEG Spectrum

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Abstract

The classification of sensorimotor rhythms in electroencephalography signals can enable paralyzed individuals, for example, to make yes/no decisions. In practice, these approaches are hard to implement due to the variability of electroencephalography signals between and within subjects. Therefore, we report a novel and fast machine learning model, meeting the need for efficiency and reliability as well as low calibration and training time. Our model extracts finely graded frequency bands from motor imagery electroencephalography data by using power spectral density and training a random forest algorithm for classification. The goal was to create a non-invasive generalizable method by training the algorithm with subject-independent EEG data. We evaluate our approach using one of the currently largest publicly available electroencephalography datasets. With a balanced accuracy of 73.94%, our novel algorithm outperforms other state-of-the-art non-subject-dependent algorithms.

Keywords: Decision prediction, motor imagery tasks, EEG, machine learning

1. Introduction

For people who have severe motor disabilities, alternative methods of communication and control are necessary. The availability of communication outlets is especially essential for patients with Locked-in syndrome (LIS), who are incapable of moving any part of their body or face except for horizontal eye movements and sometimes upper eyelid movements (Bauer et al., 1979). There are multiple conditions leading to LIS, among others, strokes and other brain lesions or multiple sclerosis. Despite their inability to communicate, most LIS patients remain cognitively intact and aware of their surroundings (Laureys et al., 2005). Since no treatment is available (Masrori & Van Damme, 2020), finding a way to communicate with the patients is a necessity so that they are not trapped inside their bodies without any communication outlets.

Over the past two decades, there has been a proliferation of studies that indicate scalp-recorded electroencephalograms (EEGs) can serve as the basis for non-muscular communication systems and control devices, commonly known as brain-computer interfaces (BCIs) (Birbaumer, 2006; Branco et al., 2021). Among the research topics in BCI is decoding yes/no decisions (Naseer et al., 2014; Peterson et al., 2005) or cursor control, which is aimed at mapping brain signals to cursor movements on a screen (Li et al., 2010; McFarland & Wolpaw, 2011). BCI-based neuroprostheses are, therefore, an application that may greatly improve the quality of life for paralyzed patients who cannot communicate. IT-enabled healthcare has made tremendous progress in recent years (Alshehri & Muhammad, 2021; Tsoi et al., 2021) and continues to be advanced by the application of modern machine learning (ML) using Big Data (Banville et al., 2021; Esteva et al., 2019). The concept of BCIs, which is based on a concept from the 1970s, thus represents a promising approach for affected individuals (Nirenberg et al., 1971; Wolpaw et al., 2002). In this context, BCI systems extend communication by using recorded brain activity (beyond traditional neuromuscular pathways) to

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enable a link between the brain and a computer (Nicolas-Alonso & Gomez-Gil, 2012). The main advantage of sensorimotor rhythm (SMR) BCI systems is that subjects can learn to generate a pattern for controlling a device voluntarily using this kind of BCI without any external stimuli, as body movements are imagined. Thus, motor imagery (MI)-based BCIs are particularly useful for people with motor impairments by enabling them to communicate and control an external device. Accordingly, they can provide great added value for rehabilitation techniques and patients with impaired neuromuscular channels (Mak & Wolpaw, 2009).

By classifying SMRs in the EEG, non-invasive BCIs can be developed, which enable direct communication between the brain and external devices (Cruz et al., 2021). SMRs arise from the modeling of MI in humans (Pfurtscheller & Neuper, 1997; Wolpaw et al., 2002), allowing users to interact with external systems in an intuitive way (Brusini et al., 2021). Especially in healthcare, BCIs allow paralyzed individuals to control, among others, computers (Li et al., 2010), robotic arms (Wolpaw & McFarland, 2004), wheelchairs (Huang et al., 2012), and even autonomous vehicles (Zander et al., 2017). During MI, the subject visualizes making a movement without actually performing it. In the employed dataset in this study, four MI tasks (Imagine movement of the left/right hand, imagine moving both hands, and imagine rest state) were performed by the participants, and to create a binary-class problem, we merged the four MI tasks into two common target classes by combining the left and right MI tasks and the up and down MI tasks.

However, because SMR patterns with their corresponding MI tasks differ in amplitudes, frequency bands, spatial distribution, and timing within and between subjects, accurate mapping is challenging. Thus, so-called inter-subject transfer learning is a long-standing problem (Roy et al., 2020). ML approaches (Blankertz et al., 2008) are often used to address this issue, yielding increasingly better performance in classification (Altaheri et al., 2021). Nevertheless, due to individual differences in EEG signals, most BCI systems are calibrated specifically for individual users, i.e., they are subject-dependent (Altaheri et al., 2021), resulting in long and strenuous training times (Aggarwal & Chugh, 2022). However, the use of real-time BCIs is of great importance for practical applications (Aggarwal & Chugh, 2022). Nevertheless, current ML approaches still show a very long calibration as well as classification time (Lotte et al., 2018). Therefore, there is a need to shorten BCI calibration times. A method that has received less attention in BCI research so far is the random forest (RF) classifier (Breiman, 2001). It offers the advantage of a short application time and resistance to outliers and artifacts. Furthermore, it could achieve the highest classification accuracies in many other domains and showed the first promising results in the context of non-invasive BCIs (Akram et al., 2015). Moreover, most approaches in scientific publications follow the traditional classification of EEG frequency bands into delta, theta, alpha, beta, and gamma bands (Mueller-Putz et al., 2015). However, promising predictions could already be made, for example, for health behavior prediction (Breitenbach, et al., 2022) by a fine-grained analysis of EEG sub-bands following Buettner et al. (2019). This subdivision could identify individual frequency sub-bands that are particularly important for classifying directional predictions for a BCI system. Our interest is to explore BCI technology as a potential solution for promoting independence in severely paralyzed individuals who require alternative methods for communication and control. Therefore, in this paper, we investigated the following research question: Is it possible to classify binary-class (Yes/No Decision) SMR-based BCI tasks subject independent, using EEG data only? Using fine-graded frequency bands and power spectral density (PSD) in the context of modern ML, we propose an RF-based classification model for EEG-based MI-BCI systems.

Our most important contributions are:

1) We develop a RF classifier to distinguish between two MI data from MI tasks for a binary-class problem in a non-subject-dependent approach with a balanced accuracy of 73.94%.
2) The model has a low average classification time of 0.256 milliseconds (0.688 seconds of classification time divided by 2,687 trials).
3) We identified the most important frequency bandwidths to classify bi-directional predictions in the EEG data. The most relevant sub-bands are all in the gamma range (25-40 Hz).

These contributions allow us to add a few things to the current state of research. First, we address the need for a subject-independent classification approach (McFarland et al., 2000). Second, with an accuracy of 73.94%, we outperform most other subject-independent models (Han & Jeong, 2021; Mattioli et al., 2021). And we show a faster approach than the data-hungry deep learning models (Kwon et al., 2020). Also, through our fine-graded analysis, we can show which frequency bands and brain regions are crucial for the analysis compared to previous work.

The paper is organized as follows: Next, we address the research background and related work. After that, we describe our ML method as well as the

applied dataset. Subsequently, we present the results of our implemented method and discuss it, including theoretical and practical implications. Finally, we draw a conclusion that contains the limitations of our work and propose possible future research directions.

2. Research background

In a MI-BCI the EEG of a subject is measured and processed to determine the brain's motor intention and translate it into a control signal. It has been found that MI generates EEG patterns similar to those associated with real movements (McFarland et al., 2000). By imagining a limb movement, certain frequency bands in the EEG signals are affected either by a decrease or an increase in power (Pfurtscheller & Lopes da Silva, 1999). As a result, these intentions are categorized as different cognitive tasks, for example, left- and right-handed movements.

2.1 Machine learning algorithms for BCIs

While in the past, most MI-based BCI systems generally used subject-dependent methods that require long calibration and training times (Ang et al., 2012), there is now a growing awareness of the need for progress in developing a subject-independent pattern classifier by combining data across several subjects. Rather than having to first train the pattern classifier on subject-specific data, the goal is to decode in real-time from brain signals associated with an individual (Ruiz et al., 2014). So far, a variety of feature extraction and classification methods have played an important part in research advancing BCI. Thereby, most of the BCIs based on EEGs are supported by ML algorithms (Lotte et al., 2018).

A widely adopted approach is decomposing EEG signals into spatial patterns, and extracting features according to a common spatial pattern (CSP) (Bentlemsan et al., 2014; Robinson et al., 2013). Based on CSP methods, advanced algorithms have been proposed.

2.1 Machine learning algorithms

As shown in Table 1., Bentlemsan et al. (2014), used the RF classifier in conjunction with Filter Bank Common Spatial Pattern (FBCSP). In another study by Anam et al. (2019), the experimental results indicated that the EEG pattern recognition with RF attained the best testing accuracy for individual finger movement among the other three tested classifiers support vector machine (SVM), k-nearest neighbor (kNN), and linear discriminant analysis (LDA). In Steyrl et al.'s (2016) study RF and regularized linear discriminant analysis (LDA) are compared. Furthermore, in a previous study (Qu et al., 2018) with a binary-class classification problem, PSD was used and an LDA, and a RF model were trained.

Table 1. Comparison of algorithms for BCI.

Reference	Algorithm	Balanced Accuracy	Drawbacks
Bentlemsan et al., 2014	FBCSP + RF	79.78%	Small dataset, subject dependency
(Anam et al., 2019)	RF	54%	Subject dependency
(Steyrl et al., 2016)	RF	76.1%	Subject dependency
(Qu et al., 2018)	PSD + RF	70%	Small dataset, subject dependency
(Lun et al., 2020)	CNN	97.28%	Large training dataset
(Mattioli et al., 2021)	CNN	50.2%	Additional training required for target individuals
(Dose et al., 2018)	CNN	58.58%	Large training dataset
(Kwon et al., 2020)	CNN	74.15%	Possible overfitting, small number of parameters

2.2 Deep learning algorithms

Additionally, Deep Learning (DL) has become increasingly popular for BCI in the last few years and could be successfully applied by researchers to classify MI EEG signals (Ha & Jeong, 2019; Mattioli et al., 2021). In the context of MI EEG-based BCI, DL techniques have been used for both feature extraction and classification (Tang et al., 2019). Lun et al. (2020) proposed a CNN architecture to classify a four-task MI dataset. The methods of MI classification described so far use intra-subject data for training. As mentioned, acquiring EEG data from target subjects is often accompanied by time-consuming and inconvenient calibration processes.

2.2 Subject-independent frameworks

In recent years, several techniques have been proposed to reduce the calibration time of a MI-based BCI system. For example, Mattioli et al. (2021) proposed a new approach based on CNN to classify four MI classes and a "baseline" class with an accuracy of 99.46%, which shows the potential of DL for MI EEG-based BCI. Dose et al. (2018) also implemented a CNN capable of classifying raw signals related to a four-task MI dataset. Kwon et al. (2020)

proposed subject-independent framework based on CNN. Despite the popularity and outstanding performance of DL frameworks, they have a black-box nature, as they do not provide any information on what led them to reach a particular decision (Adadi & Berrada, 2018). In contrast, RF classifiers can indicate which variables are decisive for the result (Buettner et al., 2019). Particularly in sensitive application areas, such as healthcare, explainability, and transparency may be especially important to ensure trust in a certain model. Furthermore, using RF classifiers, it is possible to extract frequency sub-band employing PSD, therefore, the model complexity is kept to a minimum while still being able to make correct predictions (Buettner et al., 2019).

In the existing literature, many different techniques for feature extraction and classification of EEG signals can be found for different applications with promising performances. However, they often employ complex architectures, require large amounts of EEG data, or have high computation times. We propose a model that extracts the most important channels and underlying fine-graded frequency sub-bands, and that is transferable to new subjects with limited calibration time.

3. Methodology

For our study, we followed the design science research approach (Hevner et al., 2004). Thereby, we first identified the problem of a missing subject-independent, efficient EEG-data classification model. Therefore, based on the given dataset we developed our machine learning model as a solution. We then demonstrated and evaluated it with the given data and communicated it with this work. As shown in Figure 1, reading the data set, data preprocessing was performed with the help of filter applications and Independent Component Analysis (ICA). PSD was then applied to the preprocessed EEG data as spectral analysis and the most important features were identified (feature importance) for subsequent classification.

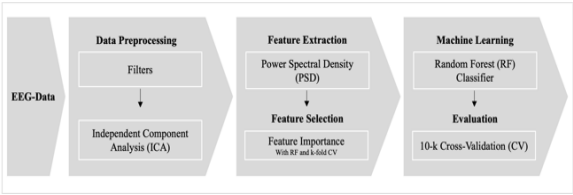

Figure 1. Methodical approach.

The data preprocessing and feature extraction with PSD were performed using the MNE library (Gramfort, 2013). A RF from the scikit-learn library (Pedregosa et al., 2011) was then used as the classification algorithm, and for the evaluation, a 10-fold cross-validation (CV) was employed. All calculations were carried out in Python 3.7.12. The RF as a ML method uses the results of many different decision trees to make the best possible predictions. These are created randomly in an uncorrelated manner and each tree makes a single decision at a time, from which the algorithm provides a final decision (Breiman, 2001).

3.1 Preprocessing

As EEG data is acquired from the scalp via different electrodes, noise or artifacts are inevitable that should be removed before further processing. Examples of biological artifacts are muscle activity, blinking eyes, eye movements, and heartbeats. Additionally, electrical noises such as those generated by computers or electric lights, or cable movements are examples of non-biological artifacts (Mueller-Putz et al., 2015). To increase the signal-to-noise ratio and thus subsequent feature extraction efficiency (Jafarifarmand & Badamchizadeh, 2019), different procedures can be employed (Steyrl et al., 2016). We first applied a notch filter to remove the power line noise (Ferdjallah & Barr, 1994).

As a second measure to mitigate artifacts, we used digital high-pass and low-pass filters (Mueller-Putz et al., 2015) with filter settings of 0.5 Hz and 50 Hz, respectively. In addition, we performed a standardized automatic independent component analysis (ICA) (Mueller-Putz et al., 2015), which is based on the blind source separation method and is suitable for EEG data (Makeig et al., 1995). ICA allows the extraction of statistically independent components resulting from a linear mixture of source signals (Bell & Sejnowski, 1995).

The initial dataset had four target classes (Left, Right, Up, Down). Thereby the imagine of opening and closing from the left- (right-) hand represents Left/Right, the imagine of opening both hands represents Up, and imagine the rest state means Down. To create a binary class problem, we merged two target classes each (Left/Right and Up/Down) into one common class. Thereby, we combined the obtained EEG signals from the opening and closing from the left- and right-hand MI task (Left/Right) for the first common class and the opening of both hands and the rest state (Up/Down) for the second common class. The first common class represents a horizontal movement (shaking of the head), for making “no” decoding. The second common class represents a vertical movement (nodding) for obtaining “yes” decoding (Andonova & Taylor, 2012).

3.2 Feature extraction and selection

To further analyze the preprocessed EEG signals in the MI-BCI system, feature extraction is an important component in reducing dimensionality and computation time (Jin et al., 2020). By using EEG spectral analysis, the time series data can be converted into frequency domain data (Buettner et al., 2019). For the spectral analysis, we employed a PSD using the nonparametric approach of Welch's method. A sliding window is applied to determine the periodogram in these segments to construct an efficient estimator based on overlapping segments. Finally, averaging all the estimates of all segments provides the result. Thereby, the major advantage of Welch's algorithm is that it makes no assumptions about the distribution of the data (Welch, 1967).

One of the goals of this work is to identify the frequency bands that are most relevant for classifying MI tasks from EEG data. Therefore, following the feature extraction criterion, it is deliberately not divided into the usual frequency bands of gamma, beta, alpha, theta, and delta (Mueller-Putz et al., 2015). Rather, the whole frequency bandwidth is divided into many small equally sized sub-bands with a step size of 0.5 Hz in each case. Finer graded frequency bands could lead to more accurate classifications due to their higher information content, which has already been successfully demonstrated in other contexts (e.g., detecting schizophrenia (Buettner et al., 2020) or evaluating the working memory (Breitenbach et al., 2021)). A maximum frequency of interest was set at 64.5 Hz for the PSD. Finally, a RF-based analysis of feature importance as measured by the average reduction in impurity across all trees was used to identify the most relevant features for subsequent classification (Menze et al., 2009).

3.3 Machine learning

Several ML classification options are available for BCI systems (Aygun et al., 2021; Janapati et al., 2021), but do not provide information on the most important predictors (Archer & Kimes, 2008). Thus, to answer which frequency bands are crucial for classifying tasks we chose the RF classifier originally developed by Breiman (2001). The RF offers several advantages. It can process a large amount of data efficiently, has a high classification accuracy, and indicates which variables are essential for its result (Buettner et al., 2019). Furthermore, RFs have already been successfully used in the context of MI-based BCIs (Steyrl et al., 2016). Moreover, RFs are especially useful for the subdivision of EEG data into finer frequency bands (Buettner et al., 2019). As described previously, the RF classifier was trained using the features that contribute most to predictive power, which were determined by the feature importance selection procedure. In this procedure, the feature importances of the individual features were added up over the 10 folds to see which features were most important on average using the arithmetic mean. Afterward, a loop was used to check with which number of the best features the RF could achieve the best results. This procedure was carried out twice. Finally, we performed hyperparameter tuning to determine the optimal values for the RF classifier. It was performed using the grid search algorithm, as it provides a simple but effective strategy (Probst et al., 2019). In our model, we tuned the 3 hyperparameters: number of trees (n estimators), maximum features (max features), and splitting quality measure (criterion).

3.4 Evaluation

As a final step, the evaluation of the classifier is of great importance, measuring how well the predictions made by the model match the observed data. This can be accomplished by methods such as hold-out or bootstrap, but CV is the best-known and most practical approach (Altaheri et al., 2021; Breiman, 1996). Therefore, we applied a k-fold CV with 10 splits to evaluate the RF classifier (Fushiki, 2011). The k-fold CV randomly divides the underlying dataset into k equally sized parts. Among the k subsamples, one is retained for validation by testing the model and estimating the prediction error, and the remaining k-1 folds are used as training data. The process is repeated k times, with each of the k subsamples used exactly once as validation data (Rodriguez et al., 2010). The resulting CV matrix then indicates how robust a model is (Kohavi, 1995).

3.5 Dataset

To validate our proposed approach, the previously described method was applied to an existing EEG-based MI dataset by Stieger, Engel, & He (2021). Using publicly available datasets, it is possible to develop MI-BCIs without EEG recordings employing ML techniques (Altaheri et al., 2021). BCI competition datasets are among the most popular MI datasets publicly available (Altaheri et al., 2021). Although these allow for comparison between studies, they are often small and simple with a maximum of nine subjects, and without including online feedback (Altaheri et al., 2021; Blankertz et al., 2006, 2007, 2008). Further examples of publicly available datasets

are from Cho et al. (2017), who acquired EEG data with 64 electrodes (full scalp coverage) from 52 subjects. However, the dataset only contains data for two classes at 36 minutes and 240 samples each. Additionally, Lee et al. (2019) presented EEG data collected from 54 subjects and a relatively high number of trials, but also only based on two classes. Since we wanted to tackle a binary-class problem with a high number of subjects to develop a model with high generalizability and minimized subject dependency we decided to use the publicly available dataset from a longitudinal study by Stieger, Engel, & He (2021) to investigate the control of SMR BCIs using our proposed model. The full dataset is available at https://figshare.com/articles/dataset/Human EEG Dataset for Brain-Computer Interface and Meditation/13123148. The employed SMR BCI dataset currently represents one of the largest and most complex (Stieger, Engel, Jiang, et al., 2021).

The dataset contains data from 64 electrodes on the scalp digitized at 1,000 Hz and filtered between 0.1-200 Hz with an additional notch filter at 60 Hz and subsequently stored for offline analysis. Using an EEG cap, the electrodes were positioned according to the internationally standardized 10-10 system. In total, EEG recordings were collected from 62 adult subjects, each of whom completed 7-11 BCI online training sessions. The dataset contains 600 hours of EEG recordings, consisting of 598 recording sessions with 269,099 trials for continuous 2D control with online feedback in up to four classes (MI-BCI tasks). During different blocks of trials, subjects controlled a cursor towards a target. Participants were asked to imagine opening and closing their left (right) hand to move the cursor to the left (right). Second, the task was to imagine the opening and closing of both hands to move the cursor upward, and finally, they should voluntarily clear their mind to move the cursor downward (Stieger, Engel, & He, 2021). This results in the 4 classes of the dataset.

4. Results

By applying the fine subdivision with a step size of 0.5 Hz, 130 frequency sub-bands could be identified. Combining this with the available 62 channels yielded 8,060 features. Only the EEG data from the second session of the subjects were used to train and evaluate the RF classifier. The second session was chosen because the first session was a training session and we wanted to reach a high subject independency which is the reason all subjects were included. In the end, we were able to reach a balanced accuracy of 73.94% (see Table 2. and Table 3.).

Table 2. Mean performance indicators over ten folds.

Performance Indicator	Value
Balanced Accuracy	73.94 %
Sensitivity (true positive rate)	77.26 %
Specificity (true negative rate)	70.62 %
Kappa	47.89 %

Table 3. Confusion matrix with mean values over ten folds.

		Prediction	
		No	**Yes**
Reference	**No**	**949.1**	394.7
	Yes	305.4	**1037.8**

In addition, the fundamental approach is that subjects using our BCI to communicate a yes/no decision based on EEG data will be asked for their consent/rejection twice to confirm their initial decision. Thereby, with the current evaluation results, the accuracy rises to 93.2% ($1-(1-0.7394)^2$). Furthermore, we achieved an average classification time of 0.256 milliseconds (0.688 seconds training time divided by 2,687 training trials). By looking at the 15 most important features we found out that only the channels T7, FP2 and PO8 were represented there. If we look at the ten most important features (82T7, 51FP2, 83T7, 50FP2, 43FP2, 28PO8, 76T7, 82FP2, 74T7, and 84T7) it is noticeable that mainly sub-bands between 50 and 80 are important which means a frequency range of 25-40Hz (lower gamma frequency) (Mueller-Putz et al., 2015).

5. Discussion

To the best of our knowledge, we are the first to develop a subject-independent algorithm to predict decisions based on binary-class MI EEG data for a BCI application employing a fine-grained EEG spectrum. Furthermore, the employed dataset has not yet been used in a BCI application. Therefore, with the achieved accuracy of 73.94%, we set a new benchmark and reach a predictive gain of 23.94%. Although our results must be confirmed on different datasets, they indicate that RF is a viable alternative to the current DL methods.

Moreover, we use a 10-fold CV instead of strictly pre-training with subject independent data and then fine-adjusting with data from the target subject. Thus, we are training the classifier with data across all subjects and sessions to diminish subject dependency.

In a recent study, Song et al. (2021) observed that there were no significant differences between these approaches and subject independence could be achieved both ways. Nonetheless, future studies are necessary to further validate this. One possible way would be to apply a leave-one-out approach to our proposed model and the underlying dataset and observe the performance changes. Additionally, EEG signals are non-stationary and noisy. Certain classifiers are sensitive to noise, while others are sensitive to overfitting. Unlike many other classifiers, RFs achieve satisfying accuracies in classification while being robust to outliers and noise. Researchers have shown in the past that this technique often performs better than other ML techniques for MI-based EEG signals (Guan et al., 2019). Moreover, RFs are efficient on large databases by providing an internal estimate of feature importance (McFarland et al., 2000). At the same time, RFs come at a comparatively lower computational cost by only needing an average model training time of eight minutes. Many previous studies require about twelve minutes of calibration data (Townsend et al., 2012). Thus, we are reducing inconvenient calibration of the BCI and time-consuming training sessions for subjects. On top of that, without the hyperparameter tuning, the training time is reduced to only 352.138 seconds (CPU: Intel(R) Core(TM) i9-10885H CPU @ 2.40GHz). However, accuracy also decreases by 2%. To strike a balance between quality and feasibility, available computing resources must be considered.

By applying PSD, we were also able to show more precisely which sub-bands within the commonly used broad frequency bands are crucial. With this finer graded analysis of the frequency bands, we were able to expand the previous literature findings by showing that gamma oscillations could contain information relevant to the field of BCI. In previous studies, it was mentioned that gamma might affect MI ability because high-frequency oscillations reflect attention and cognitive functions (Uhlhaas, 2009). Consequently, our findings offer a deeper understanding of the relevant frequency sub-bands in binary classification. Therefore, we may stimulate further research to analyze these more finely graded frequency sub-bands for decoding MI-BCI tasks.

6. Conclusion

In this study, we propose a non-subject dependent ML model for an EEG-based binary-class MI-BCI task employing a fine-grained EEG spectrum. By using the most predictive sub-bands based on RF feature importance we achieved a balanced accuracy of 73.94%. This shows the potential of the model to predict directional binary-class MI solely from EEG data. Our results open a new perspective in binary-class direction prediction of BCI systems and encourage further and specific analysis of the identified sub-bands as well as brain regions. The method we propose also has practical relevance as paralysis poses both personal limitations and societal challenges for affected individuals (Zabcikova et al., 2022). Nonetheless, the practical real-world application is still constrained due to limited performance and classification time, but feasible. With the further development of non-invasive BCI systems, there is the possibility that individuals with impaired motor skills will be able to communicate with their environment through external technologies, thus greatly enhancing their quality of life in many areas. Therefore, our approach contributes significantly to the field of IT-enabled healthcare (Alshehri & Muhammad, 2021; Tsoi et al., 2021).

6.1 Limitations

Inevitably, there are also limitations to our proposed method. Although we achieved high internal validity due to the application and evaluation by means of a 10-fold CV, there is a lack of external validation of the proposed model. For this reason, applying our algorithm to datasets containing EEG-based binary-class sensorimotor data is needed. In addition, only one of the up to eleven available sessions of the 62 subjects in the dataset have been used to train and test our model, limiting our internal validity.

6.2 Future Work

In the future, we will further train the RF classifier with the EEG signals from the remaining trials to enhance the classification accuracy and generalizability of the proposed model. Moreover, the proposed methodology only used the automatic standardized ICA, which can be extended and specified individually in the future. The promising results suggest that the method may be applicable to assistive technology applications. However, there are crucial points to address from an application perspective. Besides the already applied hyperparameter tuning, further optimizations such as the combination with multiple models using ensemble learning (Altaheri et al., 2021) could be integrated and tested to further increase the accuracy of the proposed model. Moreover, future research should explore methods that evaluate classification output reliability

in an unsupervised manner to compute the optimal time of decision throughout the evaluation process.

In the future, we will test our model on other datasets for generalizability, especially on data acquired from paralyzed patients as they are addressed by our solution. Also, the performance of other state-of-the-art approaches on our given dataset should be compared to our results. Furthermore, we need to try to minimize the effort of data acquisition for our approach, by testing it with even fewer subjects.

Additionally, to further increase the classification performance, subject-specific training of the global model could be employed. In this regard, it might be interesting to use a large amount of cross-subject and -session source data and a few seconds of training data of target subjects for calibration (Song et al., 2021). We, therefore, encourage other researchers to use the dataset in their studies to advance the development of BCIs.

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