1 The Promise of Deep Learning for BCIs: Classification of 2 Motor Imagery EEG using Convolutional Neural Network

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9

10 Abstract

11 Motor Imagery (MI) is a mental process by which an individual rehearses body
12 movements without actually performing physical actions. Motor Imagery Brain-
13 Computer Interfaces (MI-BCIs) are AI-driven systems that capture brain activity
14 patterns associated with this mental process and convert them into commands for
15 external devices. Traditionally, MI-BCIs operate on Machine Learning (ML)
16 algorithms, which require extensive signal processing and feature engineering to
17 extract changes in sensorimotor rhythms (SMR). However, in recent years, Deep
18 Learning (DL) models have gained popularity for EEG classification as they provide a
19 solution for automatic extraction of spatio-temporal features in the signals. In this
20 study, EEG signals from 54 subjects who performed a MI task of left- or right-hand
21 grasp was employed to compare the performance of two MI-BCI classifiers; a ML
22 approach vs. a DL approach. In the ML approach, Common Spatial Patterns (CSP)
23 was used for feature extraction and then Linear Discriminant Analysis (LDA) model
24 was employed for binary classification of the MI task. In the DL approach, a
25 Convolutional Neural Network (CNN) model was constructed on the raw EEG

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26 signals. The mean classification accuracies achieved by the CNN and CSP+LDA
 27 models were 69.42% and 52.56%, respectively. Further analysis showed that the DL
 28 approach improved the classification accuracy for all subjects within the range of 2.37
 29 to 28.28% and that the improvement was significantly stronger for low performers.
 30 Our findings show promise for employment of DL models in future MI-BCI systems,
 31 particularly for BCI inefficient users who are unable to produce desired sensorimotor
 32 patterns for conventional ML approaches.

33

34 **Keywords: motor imagery (MI), brain-computer interface (BCI), artificial**
 35 **intelligence (AI), EEG, machine learning (ML), deep learning (DL),**
 36 **convolutional neural network (CNN), linear discriminant analysis (LDA), BCI**
 37 **inefficiency**

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1 Introduction

Motor Imagery (MI) is a dynamic experience where the user contemplates mental imagination of motor movement without activation of any muscle or peripheral nerve. A Motor Imagery Brain-Computer Interface (MI-BCI) serves as a system that converts brain signals generated during such imagination into an actionable sequence ([Alimardani et al., 2018](#); [Cho et al., 2018](#); [Millán et al., 2010](#); [Pfurtscheller & Neuper, 2001](#))

MI-BCI systems mainly utilize electroencephalogram (EEG) for measurement of brain activity ([Lebedev & Nicolelis, 2017](#)). EEG provides high temporal resolution, can be portable, is relatively low cost and represents synchronous electrical signals produced by the brain ([Lebedev & Nicolelis, 2017](#)). However, the recorded EEG signals are non-stationary and suffer from a low signal-to-noise ratio (SNR) and poor spatial resolution. Therefore, in order to employ them in a BCI system, it is necessary to apply advanced signal processing techniques to clean the data from artefacts and extract relevant spatial, temporal and frequency information from the signals for the classification problem ([Bharne & Kapgate, 2014](#)).

Traditionally, MI-BCIs operate on machine learning (ML) algorithms in which spatial features associated with movement imagination are recognized. The imagining of a left or right body movement is accompanied by a lateralization of event-related (de)synchronization (ERD/ERS) in the mu (7-13 Hz) and beta (13-30 Hz) frequency bands of EEG signals ([Pfurtscheller et al., 2006](#); [Avanzini et al., 2012](#); [Barros & Neto, 2018](#); [Wang et al., 2019](#)). This brain activity feature serves as an input to the ML algorithm classifying the imagined body movements. Therefore, the system relies on the user to consciously modulate their brain activity such that the lateralization can be detected. It is shown that fifteen to thirty percent of users cannot accomplish

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63 distinctive brain waves such that the classifier reaches accuracy above 70%. This is
64 called ‘*BCI illiteracy*’ ([Allison & Neuper, 2010](#)) or ‘*BCI inefficiency*’ ([Thompson,](#)
65 [2019](#)), where a user is considered unable to control a BCI, even after extensive
66 training. But the issue of BCI inefficiency might be argued more nuanced, as
67 successful BCI control depends on a synergy between man and machine, and
68 therefore enhancements on both sides are needed to reach efficient control
69 ([Thompson, 2019](#)).

70 In almost half of MI-BCI studies ([Wierzgala et al., 2018](#)), the mu suppression
71 lateralization is picked up by the Common Spatial Pattern (CSP) algorithm that
72 linearly transforms EEG data into a subspace with a lower dimension in which the
73 variance of one class (the imagined side) is maximized while the variance of the other
74 class is minimized ([Khan et al., 2019](#); [Shen et al., 2017](#)). The output of the CSP filter
75 is then used as an input for a ML algorithm, such as linear discriminant analysis
76 (LDA), support vector machine (SVM), or logistic regression (LR) to distinguish
77 EEG patterns associated with motor imageries ([Miao et al., 2020](#)). LDA is a very
78 popular model for binary classification of the MI task ([Yuksel & Olmez, 2015](#)); it
79 works on the concept of minimizing the ratio of within-class scatter to between-class
80 scatter while keeping the intrinsic details of the data intact ([Shashibala & Gawali,](#)
81 [2016](#)). Hence, LDA creates a hyperplane in the feature space based on evaluation of
82 the training data to maximize the distance between the two classes and minimize the
83 variance of the same class ([Aydemir & Kayikcioglu, 2013](#); [Hasan et al., 2015](#)).

84 Although, ML techniques are commonly used for binary classification of MI-BCIs
85 systems, they are extremely vulnerable to variability between subjects and drifts in the
86 brain signals ([Millán et al, 2010](#)). ML techniques do not work well under the
87 influence of noise and outliers, which are difficult to segregate from the primary data

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88 ([Müller et al., 2004](#)). Additionally, the performance of ML classifiers is highly
 89 dependent on the type of feature extraction technique that is used ([Hsu, 2010](#)). More
 90 importantly, they suffer from the ‘*curse of dimensionality*’ and are therefore highly
 91 susceptible to overfitting ([AlZoubi et al., 2008](#)). The curse of dimensionality stems
 92 from an imbalance between the number of extracted features and the number of
 93 training EEG patterns (i.e. number of subjects). In order to extract relevant
 94 information from the EEG data, multiple feature extraction techniques are adopted,
 95 which add more and more dimensions to the feature space ([AlZoubi et al., 2008](#); [Lotte](#)
 96 [et al., 2018](#)). This creates a situation in which the features vastly outnumber the
 97 observations, resulting in overfitting and an erroneous model performance. Therefore,
 98 ML approaches require yet another step of feature selection for reduction of
 99 dimensionality in the training data, which yields additional computational costs in
 100 terms of memory usage and CPU time.

101 Deep Learning (DL) classifiers are a promising alternative to address the complexity
 102 of EEG signals, as they can work with raw data and directly learn features and capture
 103 structure of a large dataset without any feature engineering or selection processes
 104 ([Albawi et al., 2018](#); [Robinson et al., 2019](#); [Wang et al., 2018](#); [Yang et al., 2015](#)).

105 Thus, the issue of information loss while generating and selecting features is avoided
 106 when DL classifiers are used ([Qiao & Bi, 2019](#)). Additionally, they can be used to
 107 stabilize the learning process by overcoming the issue of noise and outliers in the data
 108 ([Al-Ani et al., 2010](#)). DL generates high-level abstract features from low-level
 109 features by identifying distributed patterns in the acquired data. Hence, DL models
 110 hold the potential of handling complex and non-linear high dimensional data ([Wang et](#)
 111 [al., 2019](#)).

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112 Past research has already established the effectiveness of the DL approach, especially
 113 Convolutional Neural Network (CNN), in classification of MI-EEG ([Tang et al.,](#)
 114 [2017](#); [Gao et al., 2018](#); [Sakhavi et al., 2015](#); [Li et al., 2020](#); [Dai et al., 2019](#); [Tayeb et](#)
 115 [al., 2019](#); [Stieger et al., 2020](#); [Zhang et al., 2021](#); [Ko et al., 2020](#); [Mane et al., 2020](#)).
 116 The advantages of CNN model include handling raw data without any feature
 117 engineering process, facilitating end-to-end learning and requiring lesser parameters
 118 than other deep neural networks ([Shen et al., 2017](#); [Albawi et al., 2018](#)). CNN works
 119 well with large datasets and can exploit the hierarchical structure in natural signals
 120 ([Schirrmester et al., 2017](#)). Moreover, CNN has good regularization and degree of
 121 translation invariance properties along with the ability to capture spatial and temporal
 122 dependencies of EEG signals ([Aggarwal & Chugh, 2019](#)). CNN can be particularly
 123 useful in classification of MI-EEG for low aptitude users. Stieger et al. ([2020](#)) showed
 124 a negative correlation between online (ML-based) performance and improvement of
 125 accuracy with CNN, which suggests that BCI inefficient users may benefit from
 126 applying a DL classifier, even more than high aptitude users. They further showed
 127 that the low performing users in the online classification did not necessarily produce
 128 the expected SMR activity during MI process, but instead produced differentiating
 129 activity over brain regions outside the motor cortex such as occipital and frontal
 130 gamma power, which could not be recognized by CSP. Therefore, DL methods might
 131 be beneficial in improving performance for inefficient users and serve as a promising
 132 tool in enhancing overall BCI usability.

133 This study aims to compare the two approaches of ML and DL in classification of MI
 134 EEG signals in a large group of 54 subjects. In most of previous studies, CNN has
 135 been compared with ML classifiers other than CSP+LDA. However, the use of
 136 CSP+LDA model is widespread in binary MI-BCI classification ([Lotte et al., 2018](#);

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137 [Nicolas-Alonso & Gomez-Gil, 2012](#); [Selim et al., 2018](#)). Hence, in this study, for
138 every subject, a CNN model (DL approach) was trained and its performance was
139 compared with the conventional CSP+LDA model (ML approach).
140 [Figure 1](#) shows sequential steps that were taken in each approach to construct a MI-
141 BCI classifier and obtain classification performances. The ‘*Signal Acquisition*’ step
142 was carried out through EEG to monitor the brain signals arising from the mental
143 image of the movement by the user. The complexity of the ML approach arises with
144 the steps involved in ‘*Pre-processing*’ and ‘*Feature Extraction*,’ whereas in the DL
145 approach, raw data can directly be fed into the model. Hence, by applying both
146 approaches to the data from 54 subjects, this study intends to answer the following
147 research question: “*Can a CNN classifier trained with raw EEG signals achieve a*
148 *higher performance than a machine learning model that runs on processed EEG*
149 *features for classification of a two-class Motor Imagery task?*”

150
151 **FIGURE 1** | An overview of MI-BCI classification using machine learning vs. deep
152 learning approaches. In ML approach, EEG signals are first pre-processed and
153 relevant features are extracted before applying a classifier. In DL approach, raw
154 signals are directly fed into the model.

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2 Methods

In order to compare conventional ML models with a DL approach in a large group of novice BCI users, EEG signals were collected from 57 subjects while they performed the MI task using an existing BCI system. Thereon, the recorded EEG signals were used to train a CNN and CSP+LDA model to conduct an offline classification of two-class MI task. The following section gives a description of the data collection procedure and details of the classification models.

2.1 Experiment

2.1.1 Participants

In this experiment, 57 subjects participated (21 male, 36 female, $M_{age} = 20.71$, $SD_{age} = 3.52$). All of them were right-handed and novice to BCI and the MI task. The Research Ethics Committee of Tilburg School of Humanities and Digital Sciences approved the study (REDC #20201003). All subjects received explanation regarding experiment procedure and signed a consent form before the experiment.

2.1.2 EEG Acquisition

Sixteen electrodes recorded EEG signals from the sensorimotor area according to the 10-20 international system (F3, Fz, F4, FC1, FC5, FC2, FC6, C3, Cz, C4, CP1, CP5, CP2, CP6, T7, T8). The right earlobe was used as a reference electrode and a ground electrode was set on AFz. Conductive gel was applied to keep the impedance of the electrodes below 50 kOhm. Subjects were instructed to sit calmly and avoid movements and excessive blinking. The signals were amplified by a g.Nautilus amplifier (g.tec Medical Engineering, Austria). The data was sampled at 250 samples/second. The noise during EEG recording was reduced by applying a 48-52 Hz notch filter and 0.5-30 Hz bandpass filter.

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180 **2.1.3 Motor Imagery Task**

181 Participants performed the MI task in four runs, each consisting of 20 right- and
 182 twenty left-hand trials. The first run was a non-feedback run, followed by three runs
 183 in which the subjects received feedback in form of a feedback bar on the computer
 184 screen. The feedback bar presented the classification certainty as computed by the
 185 g.tec BCI classifier, which relies on the CSP+LDA approach. The classifier was
 186 calibrated for each subject based on the data of the latest run while the subject took a
 187 break between the runs.

188 In total, participants performed 120 MI trials. Each MI trial took eight seconds. The
 189 timeline of each trial is shown in [Figure 2](#). It started with a fixation cross that was
 190 displayed in the center of the screen for three seconds. In the next 1.25 seconds, a red
 191 arrow cued the direction of the trial; the subject had to imagine squeezing their left
 192 hand if the arrow pointed to the left and their right hand if the arrow pointed to the
 193 right, without tensing their muscles. During the last 3.75 seconds, the calibration run
 194 showed the fixation cross again (see [Figure 2a](#)), while the feedback runs showed a
 195 blue feedback-bar indicating the direction and certainty of the algorithms'
 196 classification (see [Figure 2b](#)). Participants were instructed to stay focused on the
 197 imagination of the movement even during the feedback and try to not get distracted by
 198 it. The end of the trial was marked by a blank screen. The rest time between trials
 199 varied randomly between 0.5 and 2.5 seconds.

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FIGURE 2 | The time course of each trial in the BCI task. (a) shows the calibration run and (b) the feedback runs. In all trials, participants saw a fixation cross and thereafter an arrow pointing to either left or right, which indicated the corresponding hand for the MI task in the trial. In feedback runs, the blue bar indicated the direction and certainty of the classifier's prediction in order to feedback to the participants. The grey area indicates the time course of the MI task.

2.1.4 EEG Dataset

The signals from three participants were not recorded in a satisfactory manner due to technical issues during the experiment. Hence, only 54 participants were chosen from the dataset for this study. An epoch of 4 seconds was selected from each trial. This epoch, targeting the MI period, started at second 4 of the trial (1 second after cue presentation) and ended at second 8 (5 seconds after cue presentation), which is in line with the study of Marchesotti et al. (2016). The selected time segment is indicated with the grey area in Figure 2.

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2.2 Machine Learning Model

The ML approach consisted of preprocessing the signals, constructing CSP filters for feature extraction and an LDA model for classification of the left vs. right classes. CSP is a feature extraction technique that selects spatial filters from multi-channel signals and then linearly transforms EEG data into a subspace with lower dimension that maximizes the variance of one class while minimizing the variance of the other class ([Khan et al., 2019](#); [Shen et al., 2017](#)). CSP algorithm is widely used in binary MI-BCIs due to its computational simplicity and improving signal to noise ratio ([Bashashati et al., 2015](#); [Guan et al., 2019](#)). The output of CSP can be used as input for the LDA classifier in order to distinguish the classes of MI task. LDA is a dimensionality reduction model that works on the concept of minimizing the ratio of within-class scatter to between-class scatter while keeping the intrinsic details of the data intact ([Shashibala & Gawali, 2016](#)). Hence, LDA creates a hyperplane in the feature space based on evaluation of the training data to maximize the distance between the two classes and minimize the variance of the same class ([Aydemir & Kayikcioglu, 2013](#); [Hasan et al., 2015](#)). LDA is very popular for binary classification of the MI task ([Yuksel & Olmez, 2015](#)).

2.2.1 Architecture

Before applying the ML model, the EEG signals recorded from the participants were pre-processed and temporally filtered to remove artifacts. Data containing bad impedance, error in recording, or excessive movement-related noise were removed (3 subjects, see 2.1.4). Then the EEG signals corresponding to the onset of MI task (second 4 to 8, see Figure 2) were selected and taken into account ([Park & Chung, 2019](#)). Thereon, Filter Bank Common Spatial Pattern (FBCSP) was used to extract

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subject-specific frequency band of 7-30 Hz from the data through the implementation of fifth order Butterworth ([Park & Chung, 2019](#); [Lotte & Guan, 2011](#)). FBCSP was used because it is instrumental in discriminating the binary classification of EEG measurements ([Ang et al., 2012](#); [Raza et al., 2015](#); [Park & Chung, 2019](#)). It should be noted that CSP is highly dependent on the selection of frequency bands, however there is no optimal solution to select the right filter bank ([Kumar et al., 2017](#)). Using a filter bank before CSP helps to improve the accuracy level of the model ([Yahya et al., 2019](#)). A wide range of 7-30 Hz is usually adopted for CSP when used for MI classification ([Kumar et al., 2017](#)). Hence, the frequency bandwidth was kept between 7-30 Hz covering the mu and beta bands that are required to analyze Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) from the MI brain signals.

After the pre-processing and filtering steps, the 120 MI trials of each participant were concatenated and randomized. CSP algorithm was performed on each participant's data using the 'scikit' package in Python ([Yuksel & Olmez, 2015](#)). CSP extracted the spatially distributed information from the output of FBCSP by linearly transforming the EEG measurements in order to define discriminative ERD/ERS features ([Ang et al., 2012](#); [Park & Chung, 2019](#); [Raza et al., 2015](#)). Once feature extraction was completed, 'scikit' package was again used to implement the LDA classifier in order to reduce the dimensionality of the sub-bands and to perform binary classification ([Vidaurre et al., 2011](#)).

2.3 Deep Learning Model

The DL model was constructed by feeding raw EEG signals directly into a CNN model.

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CNN is a feed-forward Artificial Neural Network (ANN) model and has a sequence of layers where every layer is the output of an activation using a differential function (Aggarwal & Chugh, 2019). In a CNN, the inputs are assembled to different layers of neurons, each representing a linear combination of the inputs (Pérez-Zapata, 2019). The learning process involves modification of the parameters by adjusting weights between different layers in order to achieve the desired output (Roy et al., 2019). The learning continues until the training set reaches a steady state where the weights become consistent and an optimal output is reached (Roy et al., 2019). During the training phase of the CNN model, different layers can extract features at a different level of abstraction (Roy et al., 2019). The initial layers learn local features from the raw input, and the end layers learn global features (Schirrmeister et al., 2017).

2.3.1 Architecture

A 2D CNN model was constructed using ‘keras’, a high-level neural networks API written in Python (Keras, 2019). Figure 3 shows the architecture of the proposed CNN model.

FIGURE 3 | CNN Architecture.

The first two components of the architecture are the number of convolution filters used and the kernel size that specifies the height (columns) and width (rows) of the

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2D convolution window. These were set to 30 and 5×5 respectively. The dimensions of the input shape applied were (1×4×4). In order to compute a network's hidden layers, activation functions should be implemented ([Goodfellow et al., 2016](#)). For this task, Rectified Linear Function (ReLU) was used. ReLU conducts simple mathematical operations, preserves characteristics that result in good generalization and is less computationally expensive than other approaches. Moreover, ReLU has the advantage of the speed and overcoming gradient leakage issue when compared with other activation functions ([Pérez-Zapata, 2019](#)).

Max pooling was added to the model in order to downsample the input and refrain from losing important data features. The size of 2×2 was used based on the works of [Dharamsi et al. \(2017\)](#) and [Abbas and Khan \(2018\)](#). The output of max pooling was flattened into a vector of input data by executing a flatten layer ([Goodfellow et al., 2016](#)). Subsequently, three dense layers were added. The first two implemented a linear function in which all inputs were connected to all outputs by a specific weight ([Ullah et al., 2019](#)). The units of these were set to 256 and 128 and were activated by ReLU functions. The final dense layer's units were fixed to 2 as this was the number of class labels in the data. Finally, Softmax was applied to the last (output) layer as an activation function, used for class classification tasks ([Goodfellow et al., 2016](#)).

2.3.2 CNN Model Compilation

The hyperparameters implemented in the 2D CNN model's compilation phase are the loss function, the optimizer and the evaluation metric. Since the dataset has two target labels (right and left), the loss function categorical cross-entropy was applied. The optimizer 'Adam' was used because it is a widely used gradient-based optimization of stochastic objective functions ([Kingma & Ba, 2014](#)). An essential parameter of 'Adam' is the learning rate, which regulates the modification of the model based on

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the error obtained from the updated weights ([Kingma & Ba, 2014](#)). For the task at hand, the learning rate was set to its default value of 0.01. The evaluation metric was set to accuracy to delineate how well the CNN model could classify left vs. right MI EEGs. ([Goodfellow et al., 2016](#)).

2.3.3 CNN Model Fit

During model fitting, a specified batch size and number of epochs need to be adopted for backpropagation to take place ([Browniee, 2016](#)). The batch size greatly influences the time to converge and the amount of overfitting ([Radiuk, 2018](#)); a big batch takes into account many samples to calculate a gradient step and therefore might slow down the model training ([Goodfellow et al., 2016](#)). On the other hand, small batch sizes can supervise variation in the distribution. The batch size for the 2D CNN model was set to 264.

An epoch in DL means that all the samples in the training set are traversing through the model once ([Browniee, 2016](#)). This helps the network to see previous data for readjusting the model parameters in order to reduce any biases. The neural network updates the weights of the neuron during each epoch ([Torres, 2018](#)). However, there is not any prescribed method to calculate how many epochs are required for a particular model. Sharma ([2017](#)) stated that different values of epochs should be tried until the learning curve of the model moves from underfitting to an optimum level and until overfitting attributes start showing up, then the subsequent epoch size should be deemed as the threshold for the model. Thus, as long as both training and test accuracies are increasing at an equivalent rate, the training of the model should continue ([TensorFlow, 2020](#)). Considering the arguments from Kingma and Ba ([2015](#)) and TensorFlow ([2020](#)), 500 epochs per subject was deemed to be the threshold for the CNN model.

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2.4 Evaluation

For the CNN model, the data was split into 80% training and 20% test data. [Tang et al. \(2017\)](#) used the same splitting variation for building their CNN model. Accuracy is defined as the total amount of correct predictions that the model made including both training and test accuracies ([Goodfellow et al., 2016](#)). Hereby, the mean accuracy over all the subjects in training and test phase was calculated in order to compare the performance of CSP+LDA and CNN models.

Additionally, we observed how the CNN model and CSP+LDA model performed subject-wise by computing the difference of the two models' accuracy for each subject. This was done to give greater validity to the findings as inter-subject variability can affect the overall performance of a classifier ([Saha & Baumert, 2020](#)).

While accuracy is the overall evaluation measure of a model, it does not fully exhibit its prediction capacity. Therefore, in addition to the overall prediction accuracy, we extracted F-score metric for each class of 'left' or 'right' MI. F-score is the harmonic mean of the precision and recall metrics and demonstrates the discriminant power of the model for each existing class in the data. Previous research has shown that the BCI user handedness plays a role in lateralization of ERD/ERS during the MI task ([Zapala et al., 2020](#)). In our study, all subjects were right-handed, therefore it was expected that the errors made by the model would be more for one MI class than the other.

3 Results

The average score of the training and test accuracies across 54 subjects were taken into consideration to report the performance level of the CNN and CSP+LDA models. The CNN model reached an average training accuracy of 80.58% ($SD = 5.01$) and an

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average test accuracy of 69.42% ($SD = 4.97$), whereas the average training and test accuracies for the CSP+LDA model were 52.54% ($SD = 5.12$) and 52.56% ($SD = 2.08$), respectively. [Table 1](#) gives a summary of these results.

TABLE 1 | Comparison between training and test accuracies of CNN and CSP+LDA models.

Model	Training Accuracy ($N=54$)		Test Accuracy ($N=54$)	
	Mean	SD	Mean	SD
CNN	80.58	5.01	69.42	4.97
CSP+LDA	52.54	5.12	52.56	2.08

The obtained accuracies for both CNN and CSP+LDA models were normally distributed as evaluated with Shapiro-Wilk test (CNN: $W = 0.98$, $p = .66$; CSP+LDA: $W = 0.97$, $p = .12$). Therefore, a pairwise t-test was employed to compare the test accuracies obtained from the DL classification method to those of the ML approach ($t(53) = 22.12$, $p < .001$). This indicated that the CNN classifier significantly outperformed the CSP+LDA approach by 15.32 to 18.38% within the 95% confidence interval.

[Table 2](#) contains the top ten accuracy rates observed in the subjects using the CNN and the CSP+LDA model. As it can be seen in this table, the highest accuracy achieved by the CNN model for a subject was 81.80%, whereas the CSP+LDA model could only reach a highest accuracy rate of 57.17%. Also, although not included in this table, it was observed that the lowest accuracy level obtained from the CNN

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379 model across all the subjects was 58.60%, which is still higher than the highest

380 accuracy rate obtained by the CSP+LDA model across all the subjects.

381 **TABLE 2** | Top ten highest classification accuracies achieved by the CNN model and

382 the CSP+LDA model.

CNN Model		CSP + LDA Model	
Participant ID	Accuracy %	Participant ID	Accuracy %
Subject 31	81.80	Subject 29	57.17
Subject 48	77.36	Subject 7	56.70
Subject 16	76.94	Subject 55	56.41
Subject 25	76.32	Subject 54	56.23
Subject 55	75.81	Subject 34	56.16
Subject 9	75.72	Subject 8	55.90
Subject 60	75.64	Subject 30	55.67
Subject 12	75.58	Subject 32	55.65
Subject 42	75.52	Subject 60	55.32
Subject 23	75.08	Subject 66	54.50

383

384 To obtain an estimation of the subject-wise performance difference between the two

385 models, the difference of the obtained accuracy from the CNN model and the

386 CSP+LDA model for each subject ($Accu_{CNN} - Accu_{CSP+LDA}$) was computed. This

387 subject-wise comparison revealed that the DL approach achieved a higher accuracy

388 level for all subjects with a minimal difference of 2.37% and maximal difference of

389 28.28%. [Figure 4](#) illustrates the number of subjects for whom the CNN model showed

390 accuracy improvement in 6 bins of 1-5%, 6-10%, 11-15%, 16-20%, 21-25% and 26-

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391 30%. From this figure, it can be inferred that the CNN model outperformed the
 392 CSP+LDA model by more than 11% accuracy for 92.59% of the participants.
 393 Therefore, it can be concluded that CNN was able to extract intrinsic features from
 394 the EEG signals and thereon, performed classification with higher accuracy level.

395
 396 **FIGURE 4** | Improvement in the accuracy rate of the subjects using CNN model
 397 against CSP+LDA in percent points (i.e., absolute difference between the two
 398 accuracies; $\text{AccuCNN} - \text{AccuCSP+LDA}$).

399
 400 Further exploration was done to investigate whether the improvement achieved by the
 401 CNN model was different across BCI users based on their initial MI skill.
 402 Traditionally, users that cannot produce desired ERD/ERS patterns to be recognized
 403 by a MI-BCI classifier are defined as low aptitude users or BCI inefficient
 404 ([Thompson, 2019](#)). Therefore, based on classification accuracy rates obtained from
 405 the CSP+LDA model, subjects were divided into two groups of Low Performers and
 406 High Performers. The split was made based on the accuracy median ($\text{Med} = 52.14\%$),
 407 resulting in 27 subjects per group. For each group, the improvement of classification

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performance from the CSP+LDA model to the CNN model was obtained per subject by subtracting the model accuracies ($\Delta Accu = Accu_{CNN} - Accu_{CSP+LDA}$). [Figure 5](#) shows the mean accuracy improvement ($\Delta Accu$) for each group. On average, the CNN model increased the accuracy rate of the Low Performers by 18.46% ($SD = 4.98\%$) and the High Performers by 15.25% ($SD = 5.81\%$). The obtained $\Delta Accu$ values for both Low Performer and High Performer groups were normally distributed as evaluated with Shapiro-Wilk test (Low Performers: $W = 0.96, p = .47$; High Performers: $W = 0.98, p = .84$). Therefore, an independent t-test was employed to compare them, revealing a significantly higher improvement of classification performance by the CNN model for Low Performers ($t(26) = 2.18, p < .05$). This result supports the notion that the CNN model can better capture intrinsic oscillation patterns associated with the MI task in inefficient BCI users, whose modulation of SMR cannot be successfully recognized by the CSP+LDA model.

FIGURE 5 | Mean difference between accuracies of CNN and CSP+LDA models ($Accu_{CNN} - Accu_{CSP+LDA}$) for Low Performer and High Performer groups. Low Performers showed significantly higher improvement in MI-BCI accuracy after using a CNN classifier.

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Finally, F-Score was calculated for each class in order to measure the predictive power of the classifiers with respect to the ‘*left*’ or ‘*right*’ MI movements. Table 3 summarizes the average and SD of F-Scores across all subjects obtained by the CNN and CSP+LDA models in regard to each MI class. As can be seen in this table, the CNN model achieved higher F-Score values for both ‘*left*’ and ‘*right*’ hand prediction compared to the CSP+LDA model. A pairwise t-test comparing the F-Scores of the two models found a significant difference for both ‘*left*’ MI movements ($t(53) = 18.28, p < .05$) as well as ‘*right*’ MI movements ($t(53) = 19.47, p < .05$) favoring CNN as a classifier beyond CSP+LDA approach.

TABLE 3 | Average F-score obtained by the CNN and CSP+LDA models for each MI class.

Evaluation Metric	CNN Model				CSP + LDA Model			
	Left Hand (<i>N</i> =54)		Right Hand (<i>N</i> =54)		Left Hand (<i>N</i> =54)		Right Hand (<i>N</i> =54)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
F-Score (%)	69.07	5.35	68.59	5.23	52.93	3.67	51.83	3.56

4 Discussion

In order for a BCI system to operate optimally for all users, it is crucial to devise a classification model that can learn from each individual’s brain signals and recognize task-related patterns with high accuracy. In this research, a CNN model was developed on a large EEG dataset from 54 subjects who conducted MI task during a BCI interaction. The main goal of this study was to validate that a DL approach employing raw EEG signals could outperform the state-of-the-art MI-BCIs, which

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often employ ML approach including CSP algorithm for feature extraction and LDA model for classification. Our results supported this hypothesis; the CNN model displayed significantly higher classification accuracy for the MI task as compared to the CSP+LDA approach for all users, but especially benefited low aptitude users by increasing their BCI performance significantly more than high aptitude users. Our results put forward the design of future BCI classifiers that facilitate better interaction between the user and the BCI system.

Until now, an in-depth analysis of a CNN model in which a large and novel dataset of raw EEG signals were directly fed to the model for classification of the MI task was still missing. Previous studies mainly focused on comparing different ML and DL models on already existing datasets. For instance, [Sakhavi et al. \(2015\)](#) employed the BCI competition IV (Dataset 2b) for multi-class classification of MI task. Their CNN model achieved accuracy level of 69.56%, whereas their Support Vector Machine (SVM) model, Multi Layer Perceptron (MLP) model and CNN+MLP model achieved accuracy level of 67.01%, 65.78% and 70.60%, respectively. Likewise, [Li et al. \(2020\)](#) used BCI competition IV (Dataset 2b) but the authors combined different feature extraction techniques with their ML and DL models to conduct comparison between these models. [Li et al. \(2020\)](#) showed that a combination of Continuous Wavelet Transform (CWT) with Simplified Convolutional Neural Network (SCNN) model achieved an average accuracy of 83%, which was 7.22%, 9.62%, 10.93%, 7.49%, 6.94%, 5.58% and 5.05 % higher than CNN+Stacked AutoEncoders (SAE), CSP, Adaptive Common Spatial Pattern (ACSP), Deep Belief Network (DBN), CSP+SCNN, Fourier Transform (FFT)+SCNN and Short Time Fourier transform (STFT)+SCNN, respectively. In another study by [Gao et al. \(2018\)](#), CSP was used for feature extraction and the CNN model was combined with Sparse Representation-

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based Classification (SRC) algorithm for binary classification of the MI task. The dataset adopted by [Gao et al. \(2018\)](#) was BCI competition III (Dataset IVa). Here the authors showed that their SRC+CNN model achieved mean accuracy of 80% ([Gao et al., 2018](#)).

Although previous studies provided promising results with a DL approach, the employed dataset by [Sakhavi et al. \(2015\)](#) and [Li et al. \(2020\)](#) only included nine subjects and the dataset used by Gao et al. (2018) only had five subjects. These datasets do not sufficiently represent the large inter-subject variability that exist among users ([Leeuwis & Alimardani, 2020](#)), which could affect the performance of the classifier. Different BCI users have a different state of mind, and hence different spatial, spectral and temporal patterns in their EEG signals ([Ahn & Jun, 2015](#)). Such variations can be due to the difference in the concentration levels of the participants while performing the MI task or baseline cognitive and psychological abilities ([Leeuwis et al., 2021](#)). Thus, it is necessary to perform BCI studies over a diverse and large pool of subjects in order to establish the broad generalizability of the findings.

In comparison to previous studies that only employed datasets with limited number of participants and trials, this study collected MI EEG signals from 54 participants in three runs (120 trials) and built a 2D CNN model on our dataset. The large number of subjects in this dataset enabled us to statistically compare the subject-wise performance achieved by the CNN model as compared to the conventional ML approach. The results showed that the CNN model achieved an average of 69.42% accuracy across all subjects, which is similar to the CNN accuracy rate achieved by [Sakhavi et al. \(2015\)](#) who used feature engineering techniques to enhance the performance of their CNN model. The accuracy level achieved by this study might initially seem insufficient when compared to [Gao et al. \(2018\)](#) and [Li et al. \(2020\)](#),

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however, this difference can be explained by various pre-processing and feature engineering techniques that were employed by these two studies. Unlike past research, this study focused on evaluating the performance of CNN model without implementing any fine-tuning techniques and by directly feeding raw data into the model. The motive for this approach was to show the efficacy of deep learning models in exploiting information from raw data without any need for feature extraction. This makes deep learning models computationally more effective by eliminating the costly steps of pre-processing and feature extraction. Additionally, such neural networks can handle noise in EEG signals better than ML models and thus can provide a more robust performance in real-time BCI applications.

The low performance obtained in the ML approach has to be compared to the online classification accuracies presented in [Leeuwis et al. \(2021\)](#), where the average classification accuracy was 74.17%. This could be explained by different architectures: The online classification of [Leeuwis et al. \(2021\)](#) was conducted by g.BSanalyze software (g.tec Medical Engineering, Austria) . In this model, baseline non-feedback data is provided to the model to calibrate the classifier for each subject before the actual classification runs. In addition, the lack of removal of bad trials in our ML approach may explain a difference in the acquired classification accuracies. Also, in [Leeuwis et al. \(2021\)](#) subjects were trained upon online classification, optimizing performance for that specific processing pipeline. Therefore, to make a fair comparison with our DL model, we employed a ML approach using offline classification with no prior training and calibration of the system.

With recent release of large scale EEG datasets (e.g. [Cho et al., 2017](#); [Lee et al. 2019](#)), there have been more attempts on employing DL models on signals from large number of participants (e.g., [Stieger et al., 2020](#); [Zhang et al., 2021](#); [Ko et al., 2020](#);

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521 [Mane et al., 2020](#)), showing the relevance and timeliness of this study in the BCI
522 field. Although these studies report the same conclusion for superiority of the DL
523 approach in MI-BCI classification, their methodology and approach in building the
524 DL model is different from our study. For instance, [Stieger et al. \(2020\)](#) trained a
525 CNN model with high density EEG (64 channel) to classify a 4-class MI task. [Mane](#)
526 [et al. \(2020\)](#) and [Ko et al. \(2020\)](#) focused on feature representations in the model;
527 [Mane et al. \(2020\)](#) employed Filter-Bank CNN to decompose data into multiple
528 frequency bands and extract spatially discriminative patterns in each band, and [Ko et](#)
529 [al. \(2020\)](#) applied a Multi-Scale Neural Network to exploit spatio-spectral-temporal
530 features for all BCI paradigms. [Zhang et al. \(2021\)](#) focused on transfer learning and
531 employed a CNN model to develop a subject-independent classifier. Therefore, while
532 our study pursues a similar goal, it dissociates itself from past research by conducting
533 a statistically supported subject-wise comparison between the DL and ML approaches
534 and also providing evidence for suitability of the DL approach for inefficient BCI
535 users.

536 As mentioned before, difference between our study and for example [Sakhavi et al.](#)
537 [\(2015\)](#), [Gao et al. \(2018\)](#) and [Li et al. \(2020\)](#) is the employment of pre-processing and
538 feature extraction techniques before applying a DL approach. The only previous study
539 that concentrated on building a CNN model for classification of binary class MI task
540 without implementing any feature engineering technique was conducted by [Tang et al.](#)
541 [\(2017\)](#), who achieved 86% mean accuracy for their CNN model. However, they
542 recorded EEG signals from 28 electrodes (as compared to 16 electrodes in this study)
543 and their subject size was only two, which does not provide a suitable representation
544 of the general MI-BCI users. Additionally, [Tang et al. \(2017\)](#) applied 8–30 Hz
545 bandpass filter on the raw data before passing them to the model and the subjects in

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their study did not receive any feedback during the MI task, which is an important factor in MI learning and online operation of the BCI systems ([Alimardani et al., 2016](#)). This makes it difficult to interpret the outcome of [Tang et al. \(2017\)](#) and can perhaps explain the higher accuracy that was achieved by them. In this study, we recruited 54 participants including MI-BCI inefficients ([Leeuwis & Alimardani, 2020](#)) and ensured that the participants were learning during the experiment through practice trials and feedback provided by the BCI system.

An important finding of this study was that the CNN model outperformed the CSP+LDA model for all of the subjects, achieving 11-30% accuracy improvement for 92.59% of the subjects. Hence, deducing from the better performance of the DL model compared to ML approach and also from previous studies ([Sakhavi et al., 2015](#); [Gao et al., 2018](#); [Li et al., 2020](#); [Tang et al., 2017](#); [Stieger et al., 2020](#); [Zhang et al., 2021](#); [Ko et al., 2020](#); [Mane et al., 2020](#)), it can be concluded that regardless of the users' ability to generate MI-specific sensorimotor oscillations, CNN models are more effective in extracting intrinsic features from EEG signals and thereon, can perform MI classification with higher accuracy level. This study also revealed that the CNN model was able to capture better understanding of the MI brain patterns in inefficient users than the CSP+LDA model. CNN significantly improved the classification accuracy for those users whose performance was lower when the conventional CSP+LDA model was adopted.

BCI inefficiency has long been seen as a human factor problem in the literature. Only recently, [Stieger et al. \(2020\)](#) suggested that DL approaches might increase accuracies for low aptitude performers, thereby enabling some of them to reach performance above the threshold of 70% accuracy. Our study supports their finding by showing that indeed; the DL approach could significantly improve the classification

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performance of low performers, supporting the arguments by [Thompson \(2019\)](#), who states that poor performance of training should not be always blamed on the user. Hereby, this study shows that designing an effective classifier using a DL approach could be more reliable in developing robust MI-BCI applications and this also overcomes the issues with BCI inefficiency. Yet another advantage of the DL approach is that it allows automatic discovery of discriminative features in raw data. Therefore, it is reasonable to consider recording and inclusion of more EEG signals from other brain regions for the model training. [Stieger et al. \(2020\)](#) showed that motor imagery processes might be extended beyond the sensorimotor cortex and mu suppression patterns, indicating that the application of deep learning might be beneficial in extracting such brain activity patterns for inefficient users. Future research can extend our findings by employing a full-scalp recording and showing how this can impact the performance of the CNN model across subjects and thereby future design of more individual-tailored classifiers for all users, especially inefficient users. The BCI performance is a product of the interplay between the BCI system and the user ([Alimardani et al., 2014](#)); therefore, the importance of user training and the ‘*human in the loop*’ cannot be overlooked. Motivation and feedback play an important role in user’s learning of the MI task ([Roc et al., 2020](#), [Alimardani et al., 2018](#)). Hence, interaction with a MI-BCI should be established on an engaging platform where the users feel engaged and enjoy the process during experimentation ([Roc et al., 2020](#); [Femke et al., 2010](#)). Additionally, detailed instructions on how to perform the mental task of MI should be provided to the users to give them a clear cognitive strategy during BCI training ([Roc et al., 2020](#)). This helps to offset the cognitive load on participants and results in stable brain signals, which in turn contributes towards

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developing an efficient BCI system ([Roc et al., 2020](#)). This study employed a classic screen-based feedback bar to provide feedback to the user during data collection. Past studies have shown that embodied feedback in form of virtual or robotic hands can improve interaction between the user and the BCI system ([Skola & Liarokapis, 2018](#); [Alimardani et al., 2016](#)). Future studies should attempt to replicate the results of this study with a more engaging and realistic feedback that could lead to generation of more distinguished brain patterns by the user at the data collection stage.

Although this study presents evidence that a DL approach outperforms a ML model for subject-specific classification of the MI task, the question remains whether the proposed CNN model will be able to perform equally well on new subjects who might have different EEG signals. A general challenge in the development and application of MI-BCI systems is their long calibration time ([Singh et al., 2019](#)). In order to reduce the calibration time or completely eliminate it, past research has proposed transfer learning in which common information across subjects or sessions is mined and used for training of the classifier to improve the prediction for a new target subject ([Azab et al., 2019](#)). However, most transfer learning methodologies focus on extracting features and adapting them from the source subject(s) to the target subject, whereas in DL models with an end-to-end decoding, the neural network itself should be able to do this with little data pre-processing ([Zhang et al., 2021](#)). Thus, it becomes important to expand this research in the future with transfer learning methods and evaluate the performance of the proposed CNN model on new targets.

In this study, classification was performed offline. This is not suitable for continuous BCI control where the classifier is constantly updated ([Wolpaw & McFarland, 2004](#)), because fluidly controlling an external device is not equal to outputting one command at the end of a trial ([Edelman et al., 2019](#)). [Stieger et al. \(2020\)](#) simulated continuous

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control by providing feedback based on the estimated class output of their CNN every 40 milliseconds and showed that CNN applied on all 64 electrodes made decisions earlier with the threshold degree of confidence and could therefore be applied to make faster decisions in continuous control compared to CNN trained on only motor area electrodes. Their proposal suggests that CNN is applicable for continuous control. Therefore, the accuracy of our classifier providing online continuous feedback should be examined in future research.

In sum, this study aimed to show the potential of DL for MI-EEG classification as opposed to the state-of-the-art ML classifiers. Our results show that compared to the conventional CSP+LDA model, the CNN model, which was trained and tested on raw EEG signals, could achieve significantly higher classification performance for all users, but especially for inefficient users. Applying DL to BCI applications is a burgeoning field, which requires large dataset for development and validation. This study dissociates itself from previous reports by employing a large dataset of 54 subjects and thus sufficiently reflecting the inter-subject variability among BCI users. One of the main advantages of using DL classifier is to eliminate the pre-processing and feature extraction stages used to build an ML classifier. Raw data collected from EEG can directly be fed into a DL classifier. Future studies should be conducted by deploying the proposed CNN model on new subjects to evaluate the performance of the model and to examine whether the same model can be employed for subject-independent classifiers.

5 Conclusion

In this research, we evaluated the benefits of DL in improving the performance of motor imagery BCIs. We extracted the performance of a CNN model trained on raw

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EEG signals from 54 subjects and statistically compared it to that of CSP+LDA, which is a popular ML classifier for binary classification of the MI task. The results revealed that the CNN model significantly outperformed the traditional CSP+LDA classifier by increasing classification accuracy for all 54 subjects in this study. Moreover, it was shown that the CNN model benefited the inefficient BCI users significantly more than high performers. Thus, we conclude that DL classifiers show promise for future MI-BCI applications for all users as opposed to current state-of-art ML-based BCI systems, which demand extensive effort in pre-processing and feature extraction and yet are impractical for some users. Future studies should further investigate the robustness of the proposed CNN model in real-time MI-BCI applications

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7 Conflict of interest

The authors declare no conflict of interest. One of the authors (NL) has a secondary affiliation with a commercial company, Unravel Research, however this does not alter our adherence to PLOS ONE policies on sharing data and materials as the data is owned by Tilburg University.

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