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Classification of motor imagery EEG signals based on an automatic analysis of neural network approach

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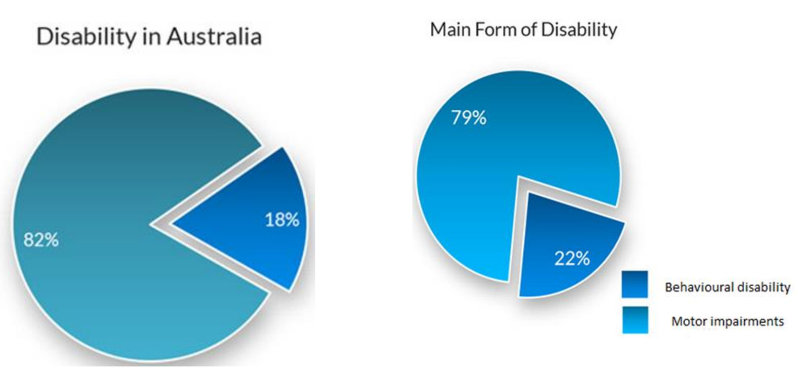
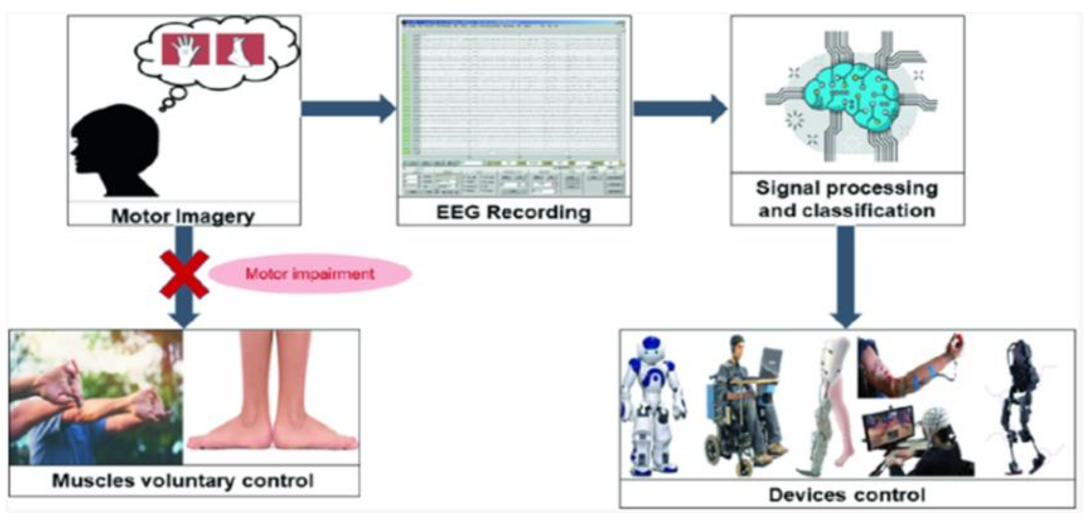
Introduction

- Around 4% people worldwide experiencing motor disability [1,2].
- In Australia, 18% people have disability [1,3].
- Around 23.3 billion AUD would be spent on this sector reported by government [3,4].
- MI based BCI through EEG signal analysis might help to improve the motor impaired people's treatment, communication, daily life and rehabilitation [5,6].



Brain computer interface (BCI) and Electroencephalogram (EEG) [7,8]



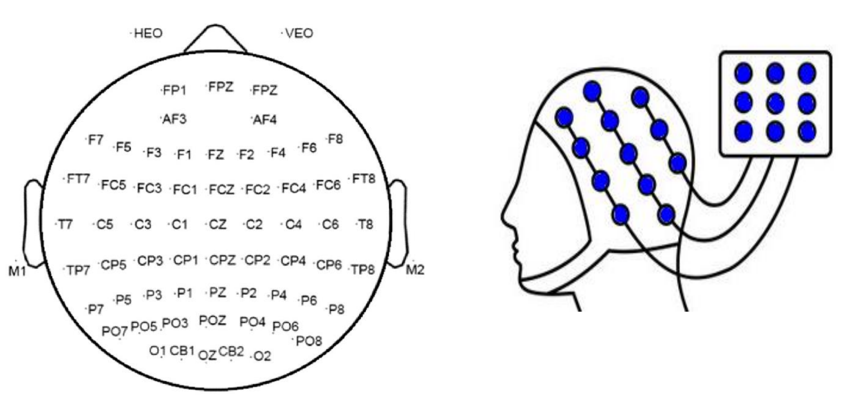
OBJECTIVES

EEG recordings typically generate enormous amounts of data with dynamic behaviour, which is difficult to manage. In order to overcome these limitations, our research aim is:

- To develop a novel artificial intelligence based automatic analysis for identifying Motor Imagery (MI) tasks more efficiently and accurately.
- To evaluate the superiority of this developed method by comparing existing prominent methods.

PARTICIPANTS AND DATA

The proposed method was evaluated using EEG databases from the BCI Competition III datasets IVa and IVb, which are available publicly.

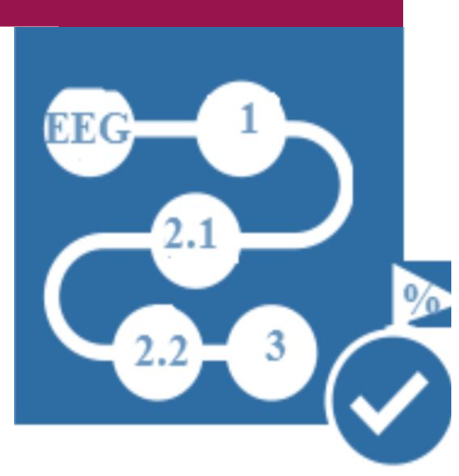


Location of the 64 electrodes in the experiments, 118 EEG channels

METHOD

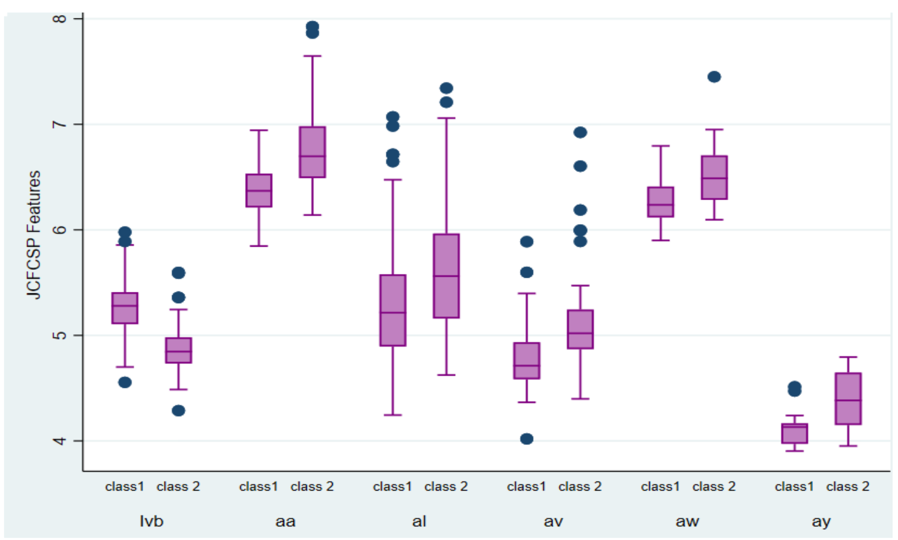
1. Signal pre-processing by Butterworth filter
2. Feature extraction by hybrid method
   2.1. Jordan Canonical Form (JCF) for Eigen value selection
   2.2. Common Spatial Pattern (CSP) to identify the spatial configurations in brain signals
3. Classification by four classifiers and see which one best performs

   The classifiers are: Bilayered Neural Network (BNN), Cubic Support Vector Machine (CSVM), Kernel Naive Bayes (KNB), and Linear Discriminant Analysis (LDA)



RESULTS

(Top Left) Figure 1: Boxplot of feature extraction data of all subjects considering left hand (class 1) and right foot (class 2) movement EEG data by applying JCF-CSP feature technique.
(Top Right) Figure 2: Comparison of classification speeds (in second) of four classifiers by subjects.



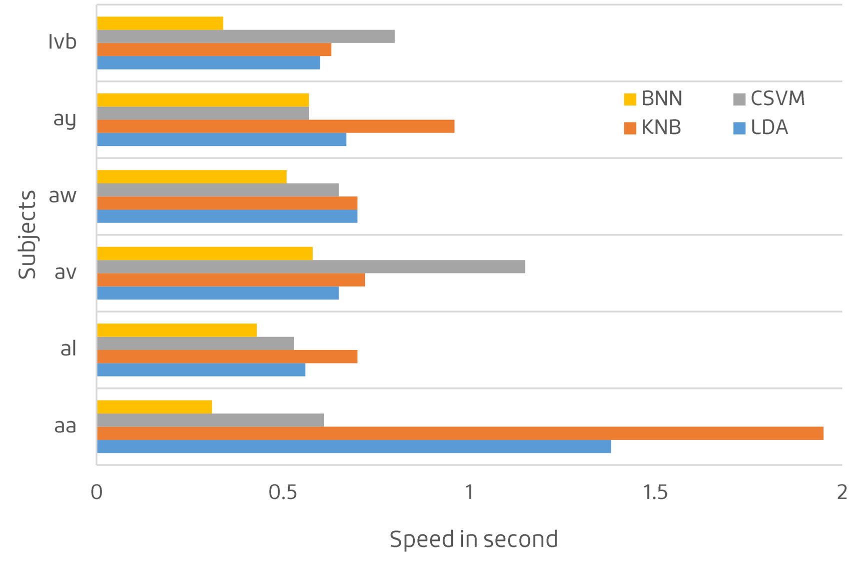


Table 1: Comparison of our proposed methods based on classifier accuracy.

	Accuracy by subjects					
Models	aa	al	ay	aw	av	IVb
JCF-CSP-BNN	100	99.6	100	100	100	100
JCF-CSP-CSVM	95.21	97.32	100	98.2	97.62	98.81
JCF-CSP-KNB	89.3	79.91	92.86	85.71	84.5	90.48
JCF-CSP-LDA	84.5	82.59	89.29	89.29	85.71	88.1

The method combination, JCF-CSP-BNN, outperforms other methods by producing the highest accuracy across all subjects, which is 100%, with the exception of subject al, which is 99.6%.

DISCUSSION

- This study suggests the JCS-CSP-BNN method for MI task classifications.
- CSP based JCF feature extraction uses Eigen values chosen by Jordan chain and block respectively, which assisted CSP algorithm to be more efficient; and BNN classifier performs most accurately on these extracted data.
- Comparing the performance of MI task (hand or foot movement intention) classification analyses between this study and well-known CSP based different types of methods that have been demonstrated for the same dataset (see Table 2), we found that our suggested model performs better.

Table 2: A comparative study of our proposed method with existing studies that analysed the same dataset.

References	Feature extraction	Classification algorithm	Accuracy (%)					
			aa	al	av	aw	ay	IVb
This Study	JCFCSP	BNN	100	99.60	100	100	100	100
Ma et al, 2023 [9]	tCSP	FDA	85.88	97.39	77.78	96.67	100	-
Gu et al, 2023 [10]	CCSP-L21	LDA	73.46	100	70.90	95.41	85.56	-
Khanam et al., 2023 [7]	CSP	MKNN	97.30	100	90.30	92.40	95.60	-
Huang et al., 2022 [11]	TWFBCSP	MVO	89.60	99.30	69.30	96.10	92.10	-
Sun et al., 2022 [12]	e-CSP	LDA	90.00	96.78	93.10	96.10	95.60	-
Padfield et al., 2021 [13]	MSMV-CSP	SVM -RBF	94.40	99.70	95.10	95.60	96.90	-
Cherloo et al. 2021 [14]	RCSSP	DT	82.14	96.42	68.87	98.21	88.88	-
Hekmatmanesh et al., 2020 [15]	DFBCSP-DSLVQ	SSVM-GRBF	93.50	98.57	81.78	93.57	96.07	-
Park and Chung, 2019 [16]	LRFCSP	SVM	98.93	93.21	81.79	93.21	97.50	-
Park and Lee, 2017 [17]	FBRCSP	Ensemble method	91.07	94.64	75.00	76.78	93.65	-

CONCLUSION

This study suggests a quick and effective machine learning based framework for categorising motor imagery intentions (hand and foot movements) using EEG data. With the help of the suggested method, JCF-CSP-BNN, motor-disabled individuals' intentions can be quickly ascertained, which can be used to benefit patients' rehabilitation, treatment, and daily activities. Thus, this framework will assist technologists in learning how software or apps can be created for the benefit of people with motor disabilities in Australia and other countries. This research can be used to create a real-time application that will help medical professionals quickly and effectively recognize MI from EEG signal data in the future.

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