Table 1: The methods of reviewed paper

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[1]	Jan 2021	MI	IV 2a, Stroke patient dataset	Filtering, segmentation, sliding window	CSP	LDA	ACC *approx* 80%, kappa = 0.6	sliding window
[2]	Jan 2021		III 4a, III 3a, IV 2a	Filtering, time windows	SEOWADE		ACC: III 4a 82.43, III 3a 90.65, IV 2a 80.12	Feature extraction fusion
[3]	Jan 2021	MI	III 3a, IV 1	Granger causality, channel selection	regularized CSP	linear SVM	ACC: 93.03 – 96.98%	channel selection
[4]	Jan 2021	MI	Experimental dataset, 11 subjects	Filtering, downsample		EEGNet + TL	ACC: avg 66.36%	Deep learning algorithm fusion
[5]	Jan 2021	simulated driving	Emergency braking intent detection in 7 subjects	ICA	CsEn + KFCS + LOOCV + KNN	SVM	ACC: avg. 83%	Feature extraction fusion
[6]	Feb 2021	MI	IV 2a	Filtering, time window, AE		Attention + CNN + BiLSTM	ACC 82.7%, kappa 0.78	Data augmentation, deep learning algorithm fusion
[7]	Mar 2021		IV 2b	Taguchi method + GRA	Hjorth	SVM	ACC: 82.58%	preprocessing innovation
[8]	Mar 2021	MI	III 1, III 3a, III 4a, IV 2	Filtering, downsample	CSP + Random Forest	Random subspace ERS + KNN	acc: III 1 99.21%, III 3a 93.19%, III 4a 93.57%, IV 2 90.32%	Feature extraction fusion, Classification algorithm fusion
[9]	May 2021	MI	IV 2b	Filtering, downsampling	Hjorth parameters + statistics methods + EMD	hybrid TL + SVM	ACC: 79.4% – 87.5% from the target domain, 78.48% for hybrid	Feature extraction fusion, algorithm fusion
[10]	May 2021		WAY-EEG-GAL dataset, IV 2a	Bandpass filtering, Class balancing cropping policy, 3D sliding window		Three branches 3D CNN	WAY-EEG-GAL,66.9 – 91.8, IV-2a 64.5	Preprocessing, deep learning

Table 1: Cont.

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[11]	May 2021	MI	IV 1, III 4a	Select channel via GA	Sparse time-frequency block common space mode (OCSB-CSP), channel selection	RBF -SVM	IV.1 84.78%, III 4a 90.80%	channel selection, feature extraction fusion
[12]	May 2021	SSVEP	32 Subjects, Group A Acc > 70%, Group B Acc < 70%	Filtering, down-sample	Chaos		Group A ACC 91.11%, ITR 170.67; Group B ACC 85.41%, ITR 152.40	
[13]	Jun 2021		SEED	sample selection		MCD-DA + TL	ACC: cross-participants 88.33%, cross-time 92.90%	deep learning algorithm fusion
[14]	Jun 2021	P300	III 1, III 2.	Baseline correction, Windsorzing, Local Binary Patterning.		Autoencoder + CNN	ACC: III 1 79.75% – 87.5%, III 2 75.1 – 82.71; avg. ITR: 16.83, 33 bits/min	Preprocessing, deep learning algorithm fusion
[15]	Jun 2021	SSVEP	Tsinghua standard dataset	BECS		CCA	ACC: 90.35%, ITR: 85.96 bit/min	Preprocessing channel selection
[16]	Jun 2021	ErrP	2015 Challenge Dataset, Horizon 2020 Program Data	Down-sampling, filtering		DCPM (DSP + CCA + pattern matching)	ACC: 76.59% and 77.10%	Algorithm fusion
[17]	Aug 2021	MI	experimental dataset, IV 2a, IV 2b	sliding window (1D CNN), channel selection, GAN		CNN + attention, TL	ACC: 93.6% for IV 2a, 87.83% for IV 2b	Preprocessing, Data augmentation, Deep learning algorithm fusion
[18]	Aug 2021	MI	IV 2a, experimental dataset	Reshape into 1D		1D CNN + GRU	ACC: 99.40% for IV 2a, 92.56% for experimental dataset	Innovative preprocessing, deep learning algorithm fusion
[19]	Sep 2021		Auditory dataset, visual datasets	ICA, filtering, sliding window		ResNet	ACC: Auditory 77%, visual 75%	Data augmentation
[20]	Sep 2021	SSVEP	own dataset	time slicing	PSD	Event-based ACA	ACC 93.47%	Algorithm fusion
[21]	Sep 2021	MI	EEG dataset: 109 subjects	(by EEGLAB)		Probabilistic Neural Network	ACC: 98.65%	Innovative classification algorithms

Table 1: Cont.

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[22]	Sep 2021	MI	IV 1		PSD + Riemann method	KNN	ACC: 74.64%	Feature extraction fusion
[23]	Sep 2021	MI	II 3, IV 2b	EMD	Fuzzy entropy + AR	SVM with SSSE	ACC: II.3 avg. 82.47%, IV.2b avg. 79.25%	preprocessing, feature extraction fusion, classification algorithms innovation
[24]	Nov 2021	SSVEP	BCI-SSVEP-Training Dataset	The Butterworth filter separates frequencies 12, 15, and 20 Hz	FBCSP	SVM	12 Hz 92.91, 15 Hz 98.95, 20 Hz 94.50, ITR 76.34 bit/min	preprocessing
[25]	Nov 2021	SSVEP and SSMVEP	own dataset	multi methods by EEGLAB	limited traversal viewable	Broad Learning System	ACC: SSVEP 96.22%; SSMVEP 74.54%	Feature extraction
[26]	Nov 2021	MI	109 subject experimental datasets	Filtering, ICA + WT	CSP	BLDA (Bayesian Linear Discriminative Analysis)	87.42	preprocessing
[27]	Nov 2021	silent speech	own dataset	downsampling, PCA + t-SNE and ICA	FFT	ResNet18 + GRU	ACC: 84.5% with pseudo-words, avg. 88%	preprocessing, deep learning fusion
[28]	Nov 2021	MI	own dataset	The filter is divided into 6 bands: 0.3 s, 0.6 s, 1 s, 1.2 s, 1.5 s, 2 sliding windows	rCSP	KNN + voting.	ACC: 78.9% (2 s window).	Preprocessing, algorithm fusion
[29]	Dec 2021	P300	own dataset	filtering, time slicing, downsampling		Multi-sample fusion SVM	ACC: 99.5% after 4 rounds	Downsampling, multi-sample fusion
[30]	Dec 2021	MI	EEG Motor Movement / Imagery; Dataset V 1.0.0	EEGLAB, Semi-automatic ICA, channel selection	ERD_AB (Alpha and Beta band between 8 – 25 Hz)	SVM	94.75	Preprocess channel selection
[31]	Dec 2021		Make online datasets public	Filtering, downsample, Split 1 s, 2 s, 3 s three short decision windows	CWT	CKNN (CNN + KNN)	92.26	Preprocessing, deep learning algorithm fusion

Table 1: Cont.

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[32]	Dec 2021	MI	own dataset	Artifacts removal, baseline correction, filtering and channel selection	Sample entropy and linear amplitude	LDA and SVM	ACC: offline 80.75%, real-time 82.45%	feature extraction fusion
[33]	Jan 2022	MI	own dataset	Filtering	mutual information + AR	SVM	ACC: Avg 82.04	Feature extraction fusion
[34]	Jan 2022		fusion of EEG and EMG signals	multi methods by EEGLAB		CNN + TL	ACC: 81.35% – 87.49%	Deep learning algorithm fusion
[35]	Jan 2022	MI	IV 2a	filtering, sliding window		WMFF (Improved EEGNet), CMFF (CNN + LSMT)	76.19, 80.46	Deep learning algorithm fusion
[36]	Jan 2022	MI	own dataset	SMOTE		1D CNN + TL	ACC: 99.38% for groups, 50% for cross-subject and TL	Data augmentation; transfer learning; deep learning algorithm fusion
[37]	Jan 2022	VR video stimuli	own dataset	channel selection, filtering, interpolation	FFT	Multi methods	ACC: cross-subject 85.01%, single subject 97.66%	channel selection
[38]	Jan 2022	MI	IV 2a, 2b and own dataset	Filtering, time window	CSP-FBLBP	SVM	ACC: avg. 82.39%, IV.2a 83.55%, IV.2b 79.72%; other data 75.99%	Feature extraction fusion
[39]	Feb 2022	RSVP	own dataset	filtering, channel selection, segmentation	STHCP (CSP + PCA)	LDA	ACC 90.7%	Feature extraction fusion
[40]	Feb 2022	SSVEP	BETA public SSVEP dataset	filtering, time slicing	FFT	PLFA-Net (CNN + SAM)	ACC 81.21%, 83.17% after DA	data augmentation; deep learning algorithm fusion
[41]	Feb 2022	SSVEP	own dataset	(by EEGLAB)	CCA + WT	SVM	ACC: 91.76%, ITR 48.92 bit/min	Feature extraction fusion
[42]	Feb 2022	MI	III 4a, IV. 1	CSR - CS	CSP	SVM	III 4a 88.61%, IV 1 83.9%	channel selection

Table 1: Cont.

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[43]	Mar 2022	MI	II 3, IV 2b, IV 2a	Data Auga (Gradient Norm Adversarial Augmentation).	Anchored-STFT	Skip-Net	II-3 Acc 90.7, Kappa 0.814; IV-2b 89.5, 81.8,76.0IV-2a 85.4, 69.1, 80.9	data augmentation, innovative feature extraction, deep learning algorithms
[44]	Mar 2022	MI	IV 2a	Euclidean spatial alignment	CSP	transfer learning, logistic regression	Avg ACC: 77%	Preprocess, algorithm fusion
[45]	Mar 2022	ME	III 3a, III 4a, IV 2a	Filtering; multi basic methods; voting strategies, Special GAN		Deep ConvNet	ACC: III 3a 79%, III 4a 76%, IV 2a 66%	data augmentation, deep learning
[46]	Mar 2022	MI	own dataset, IV 1	segmentation, down-sampling, filtering	FFT + UMLDA (Uncorrelated Multilinear Discriminant Analysis) + CSP (Tensor-Based Frequency Features Combination, TFFC)	SVM	ACC: own 70.61%, IV 1 88.79%	Feature extraction fusion
[47]	Mar 2022	P300	Home Control	Downsample, filtering		EEG -TCFNet	Subject-dependent ACC: 91.2%; subject-independent ACC: 68.2%	Deep learning algorithm fusion
[48]	Apr 2022		DEAP	filtering	BGWO, Hurst index, WPD	Bi-LSTM	ACC: Valencia 99.45%; arousal 96.67%; liking 99.68%	Feature extraction fusion, Deep learning algorithms
[49]	Apr 2022	Visual stimuli	dataset from Stanford Digital Repository	AEP, Interpolation, boundary clipping		EEG-Conv-Transformer (improved Conv-Transformer)	ACC: 88.78% for 4 heads, 89.64% for 12 heads	Deep learning algorithm fusion
[50]	Apr 2022		STEW dataset	Filtering, Artifact Subspace Reconstruction, ICA		EEG-TNet (Time-Fixed Convolutional + BiLSTM)	ACC: 99.21% – 99.82%	Preprocessing, deep learning algorithm fusion

Table 1: Cont.

Ref.	Month and Year	Paradigm	Dataset	Pre-processing	Feature Extraction	Classification Algorithms	Indicators	Main Direction
[51]	Apr 2022	MI	II 3, III 3b, IV 2b	ACGAN, S transform, frequency slicing		CNN-ELM	For ACC: avg. 83.5%; II.3 up to 92.1% – 94.64%; III.3b avg 83.50%; IV.2b 78.2%	Data augmentation, Deep learning algorithm fusion
[52]	Apr 2022	P300	Spelling BCI competition III Dataset 2	time slicing, fitering		IncepA-EEGNet (Inception block + attention)	ACC 75.53 – 79.14, ITR 21.59 – 33.44 bits/min	Deep learning algorithm fusion
[53]	May 2022	MI	IV 2a, High Gamma Dataset	sliding window for DA		DSC-ConvLSTM	ACC: 73.7% in IV 2a, 92.6% in HGD	data augmentation; deep learning algorithm fusion
[54]	Jun 2022		SEED, DEAP	filtering, downsampling, SLORETA		Bayes + DGCNN	ACC: 99.25%	preprocessing, deep learning fusion
[55]	Jun 2022	P300	IV 2a	EA alignment, channel selection		attention + CNN	ACC: 86.03%	preprocessing, channel selection, deep learning fusion
[56]	Jun 2022		DEAP	filtering, ICA, sliding window		CNN	ACC: 95.15% for subject-dependence, 88.28% for subject-independence	deep learning fusion
[57]	Jun 2022	P300	own dataset	filtering, baseline correction		LR-CNN	ACC: 91.9% – 95.6%	deep learning fusion
[58]	Jun 2022	P300	own dataset	basic methods, ICA, segmentation		SAST-GCN	ACC: 90.55%	preprocessing, deep learning fusion
[59]	Jun 2022	c-VEP	c-VEP BCI Dataset	multi methods	Riemann	MDM	ACC: 90.39%	preprocessing + feature fusion
[60]	Jun 2022	P300	II 2b, III 2, own dataset	basic methods, channel selection (RSBSBL Algorithm)		BLDA	channel selection	
[61]	Jul 2022	MI	IV. 2a	LSTM-AE	CSP		ACC: 60.66% – 97.76%	innovative preprocess

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