UNIVERSITAS GADJAH MADA

Improving Electroencephalogram Based Motor Imagery Classification Using Granular Ensemble Learning

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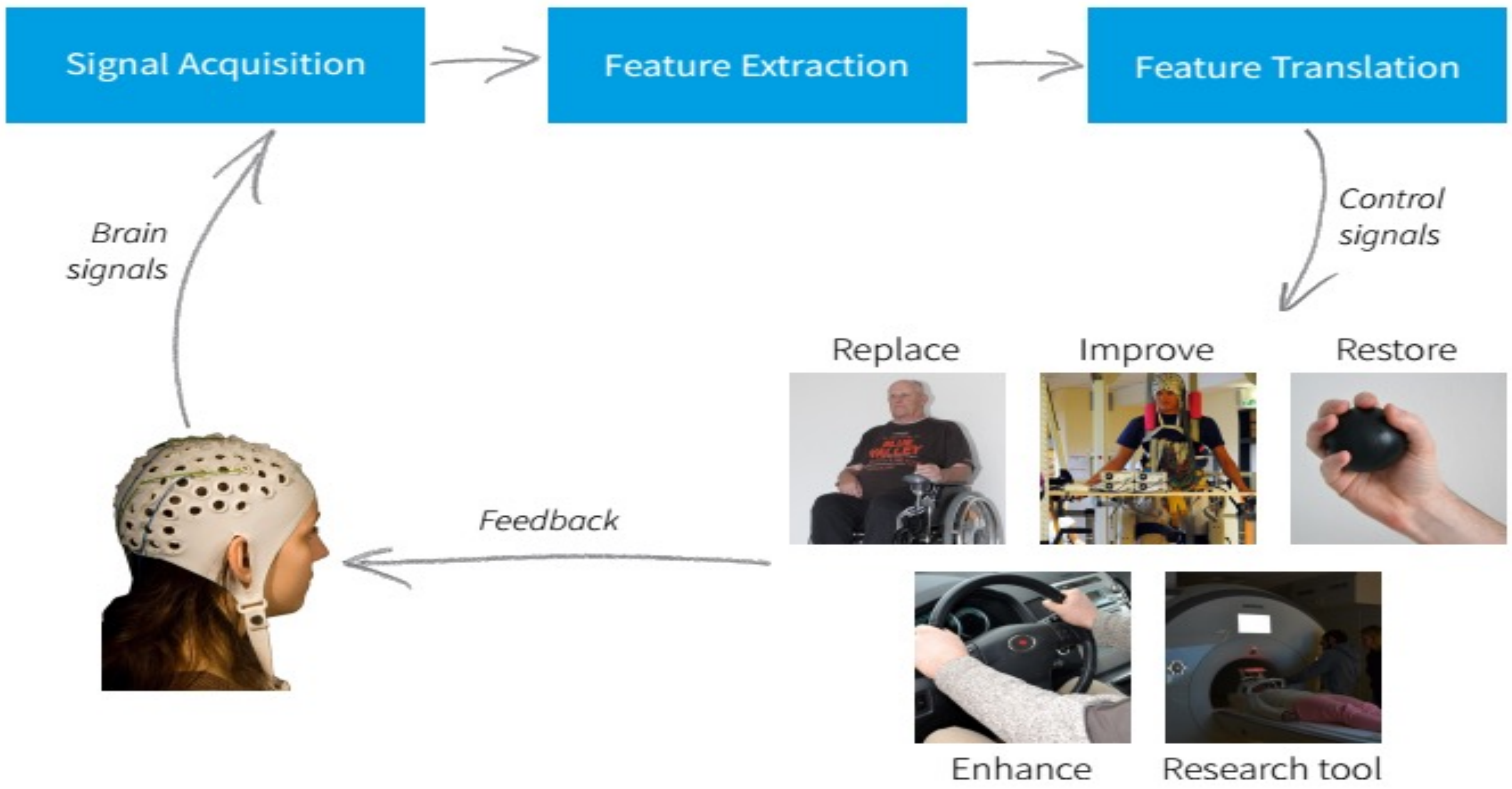
at Indonesia Association for Pattern Recognition (INAPR) Weekly Seminar

7 January 2022

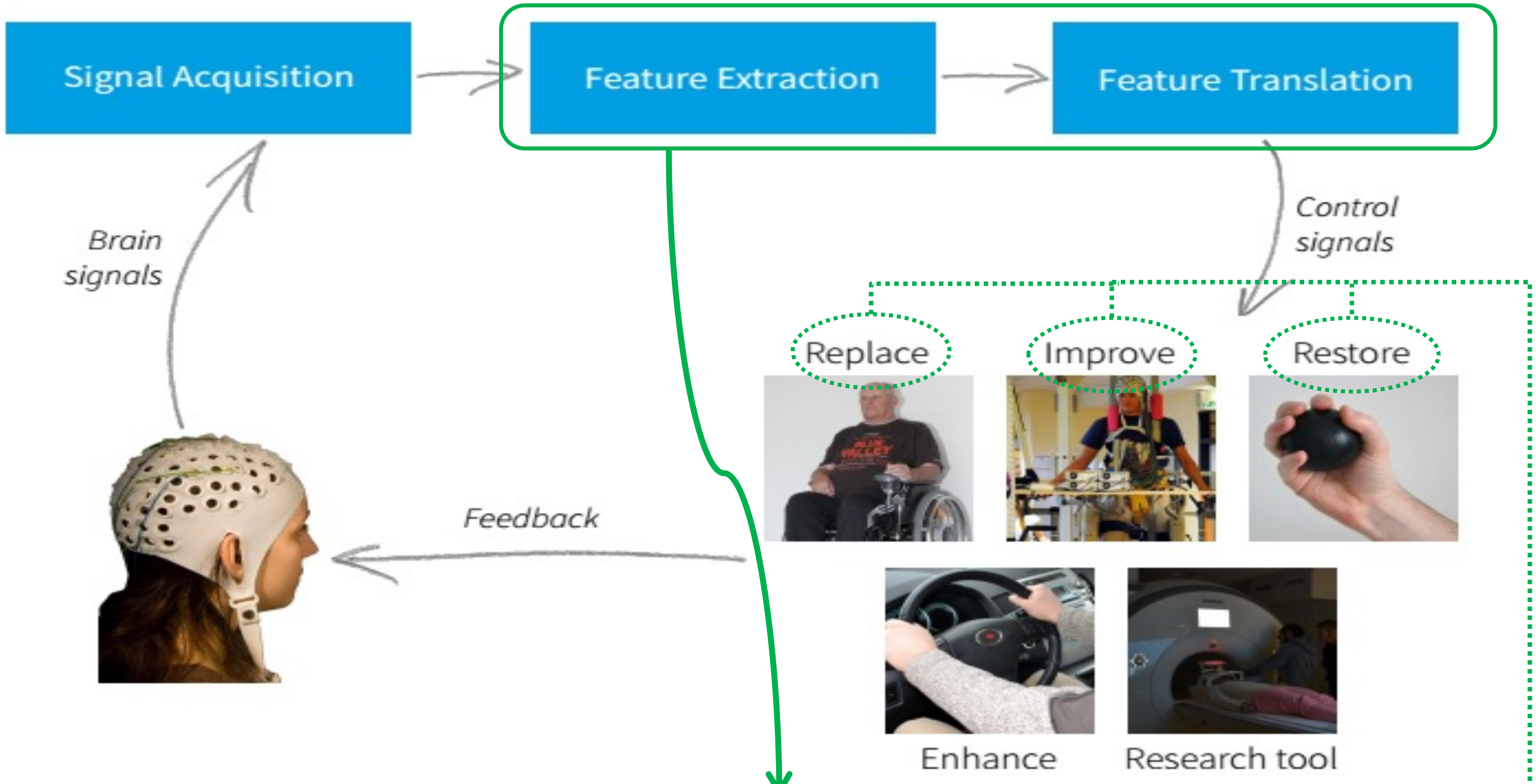
1. BCI ***Overview***

BCI **Overview**



(BNCI Horizon 2020)

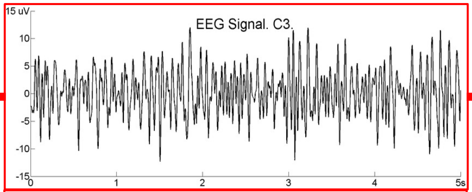
Research *Things of Interest*



EEG based Motor Imagery in BCI

2. Research ***Problem****,* ***Objective****,* *and* ***Contribution***

*Research **Gaps** (RGs)*



Nature of EEG Signal

Subject-dependent

(Kayikcioglu & Aydemir, 2010; Saha et al, 2017; Li et al., 2018)

- » **no specific feature extraction algorithm and classifier** with a high accuracy for all the subjects (Belwafi et al., 2019)
- » the **optimal accuracy** results were **quite variable**, which demonstrated **substantial inconsistency** (Li et al., 2018)
- » the **classification performance of all subjects difficult to improve** due to **differences among subject** (Luo et al., 2019)

Inconsistent detection caused by subject-dependent problem

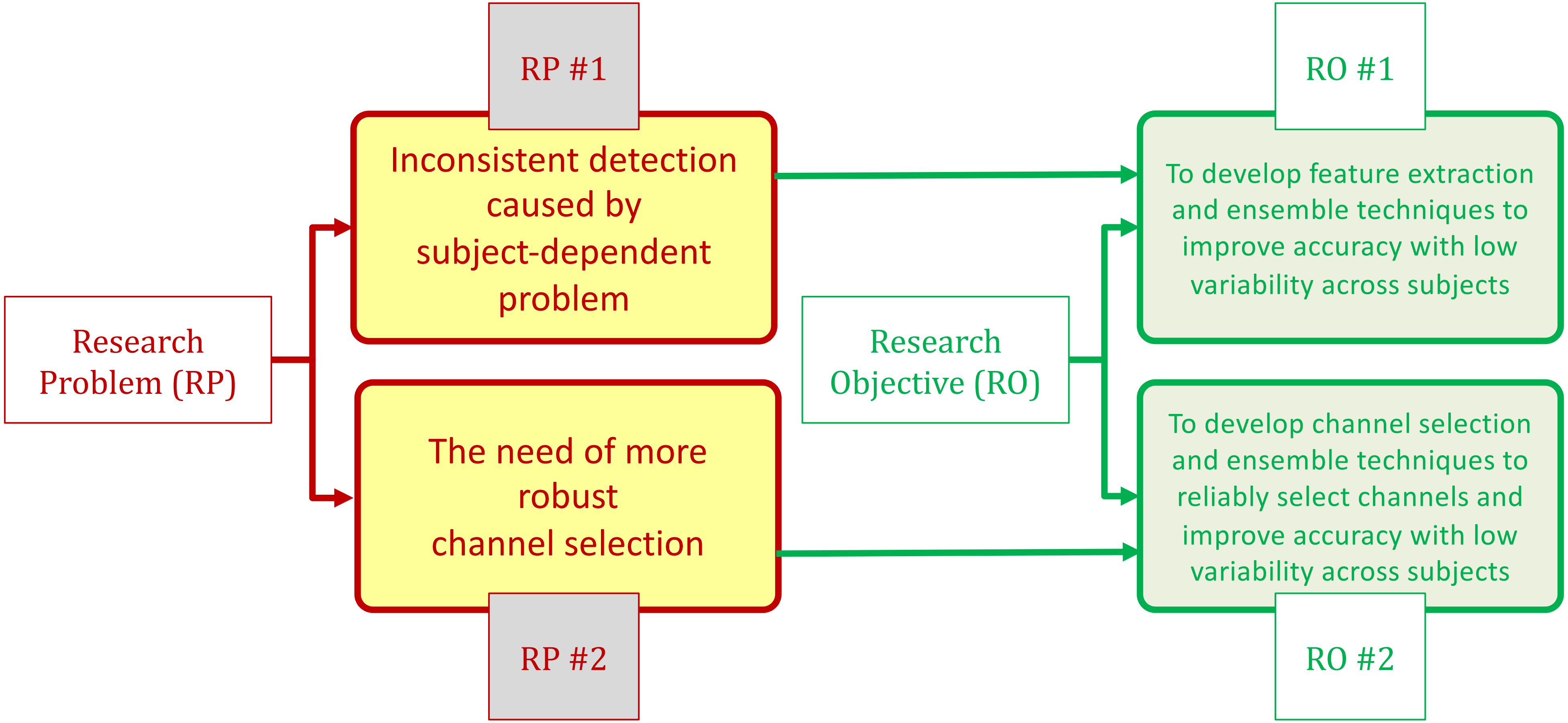
Multi-channel

(Miao et al., 2017)

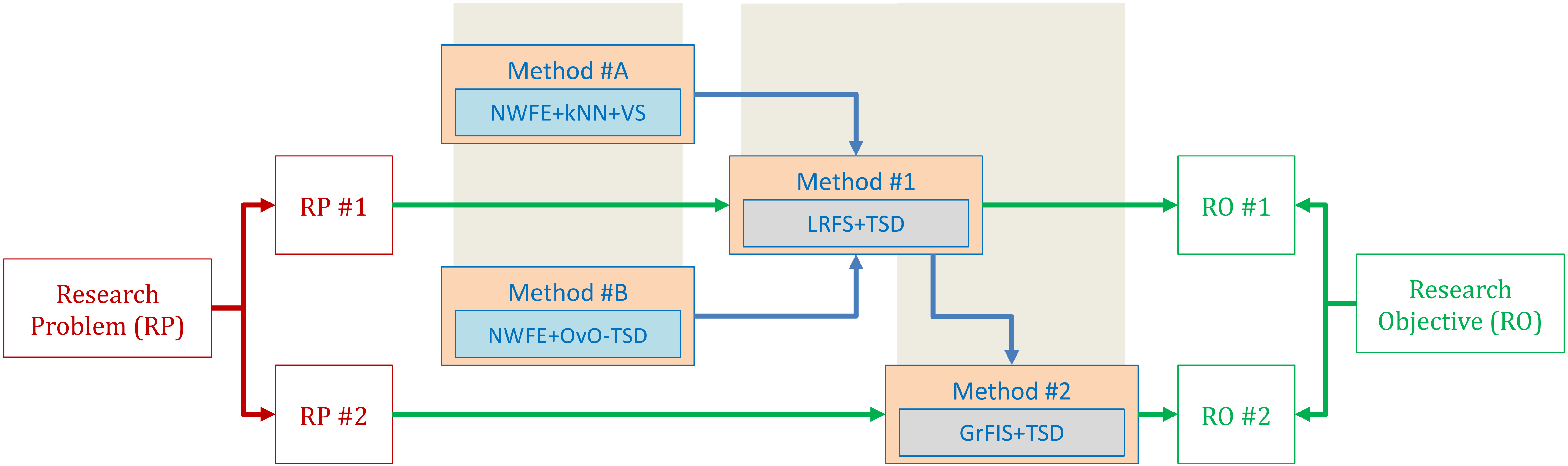
- » the estimated **optimal number of channels vary with subjects** (Y. Yang et al., 2017)
- » Multi-channel EEG signal may consists of **irrelevant and redundant channels** that **increase the computation burden** and **reduce the recognition accuracy** (Miao et al., 2017)
- » the distributions of **selected channels were different under different frequency band** (Feng et al., 2019)

The need of more robust channel selection

Research Problem and Research Objective



The Proposed Methods

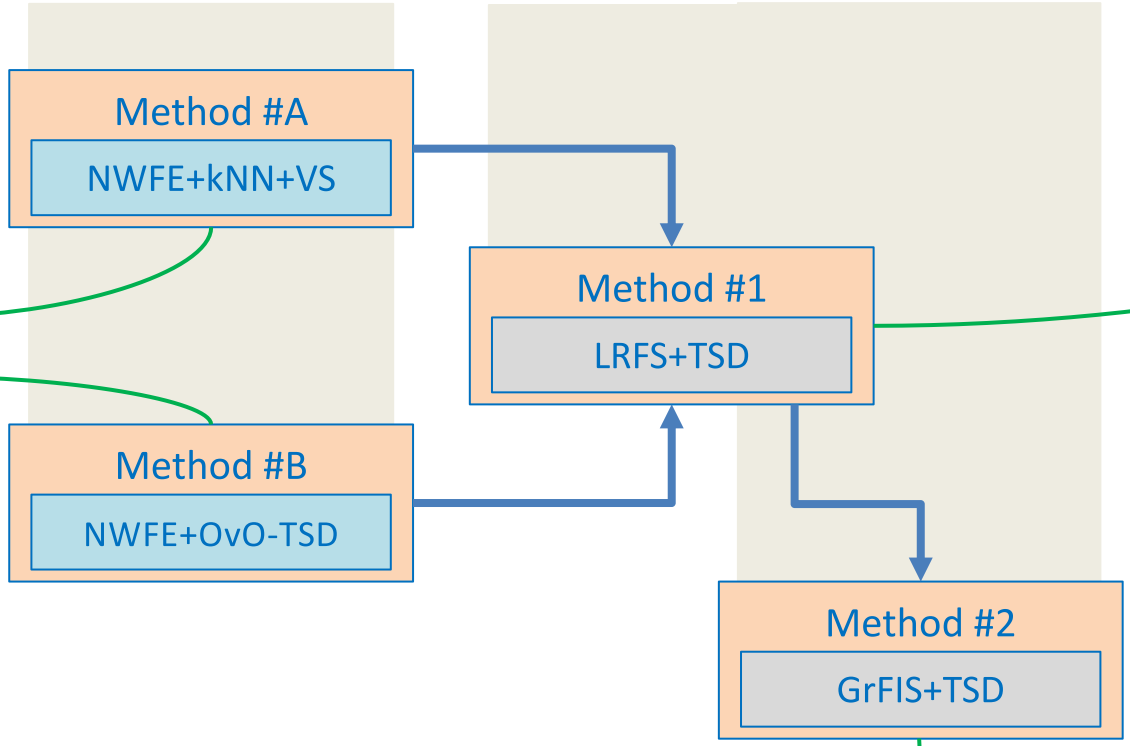


NWFE = Narrow Window Feature Extraction; TSD = Two Stage Detection; GrFIS = Granular Feature-Instance Selection
OvO = One versus One; LRFS = Logistic Regression Feature Selection; VS = Voting Scheme.

The Proposed Methods **Contributions**

Wijaya, A., Adji, T. B., & Setiawan, N. A. (2018). Narrow window feature extraction for EEG-motor imagery classification using k-NN and voting scheme. International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), 2018-Octob, 167–172.

Wijaya, A., Adji, T. B., & Setiawan, N. A. (2020). Improving multi-class EEG-motor imagery classification using two-stage detection on one-versus-one approach. Communications in Science and Technology, 5(2), 85–92.

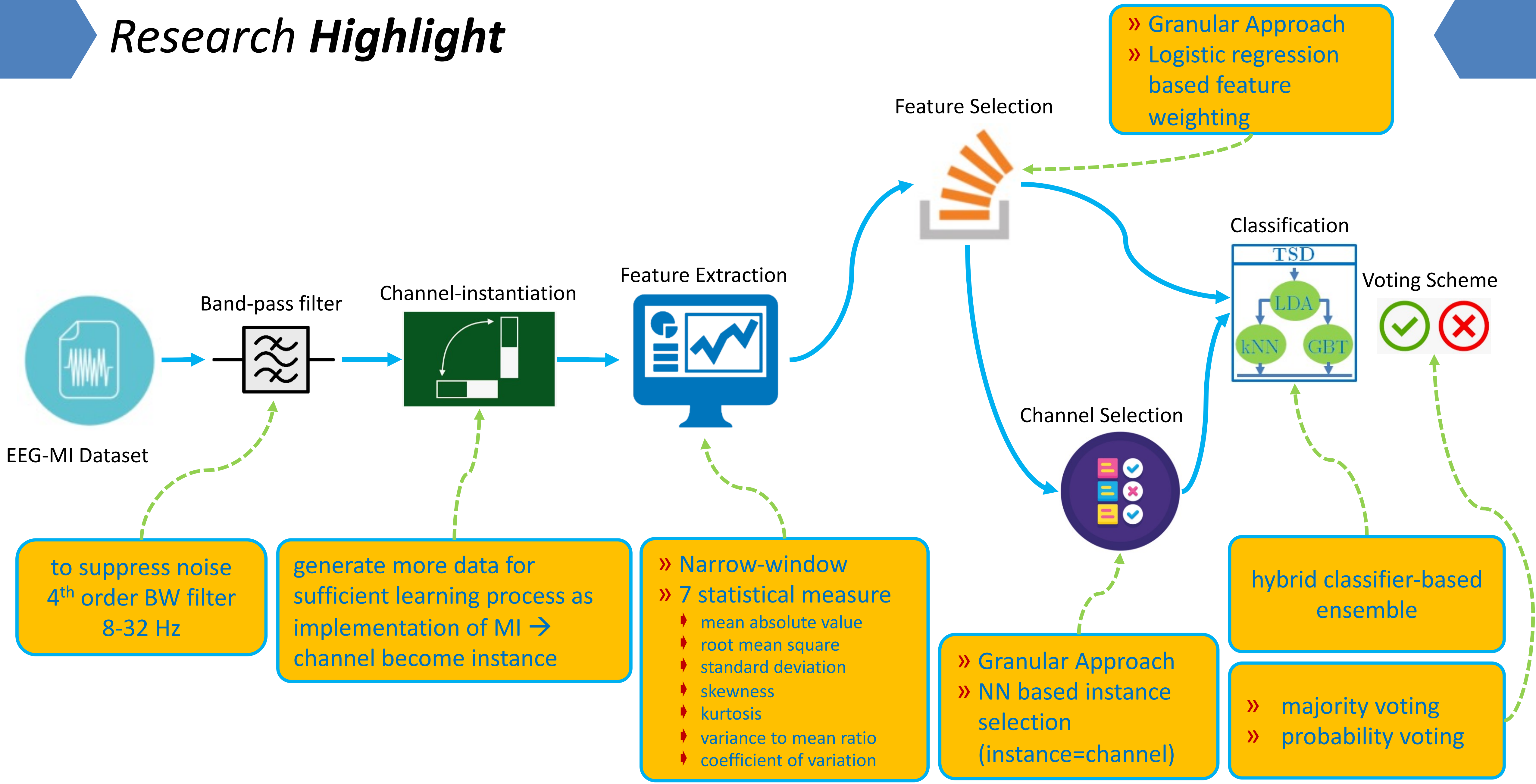


Wijaya, A., Adji, T., & Setiawan, N. (2021). Logistic Regression based Feature Selection and Two-Stage Detection for EEG based Motor Imagery Classification. International Journal of Intelligent Engineering and Systems, 14(1), 134–146.

Wijaya, A., Adji, T., & Setiawan, N. (n.d.). Robust Granular Feature and Instance Selection for EEG based Motor Imagery Classification. *In preparation.*

3. Research ***Highlights***

Research *Highlight*



Datasets

- BCI competition III – Dataset IVa
  - 2-class (Left Hand and Foot)
  - 5 subjects
  - 118 channels, 280 Trials for each Subject
- BCI competition IV – Dataset 2a
  - 9 subjects
  - 22 channels, 288 Trials for each Subject
  - » 2-class → Left Hand, Right Hand
  - » 4-class → Left Hand, Right Hand, Foot, Tongue
    - Inter-subject inter-session
    - Cross-subject inter-session

2-class classification

multi-class classification

Evaluation

Evaluation aspects:

- *Effectiveness* → Accuracy; Kappa coefficient
- *Detection variability* → Standard deviation; Consistency measure
- *Computing Efficiency* → Execution time
- *Significance test* → Bonferroni-Dunn test; Nemenyi test

4. The Experimental ***Results***

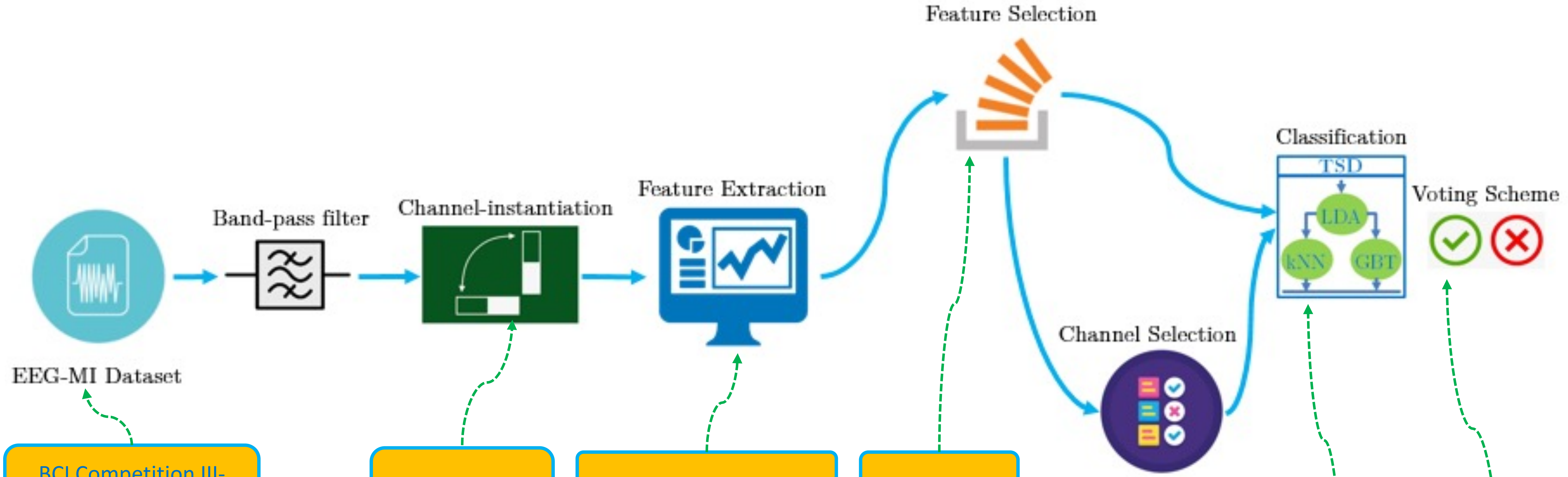
Summary *of the Proposed Methods*

Methods	Dataset			Aims
	❶	❷	❸	
NWFE+kNN+VS	✓			investigate the effectiveness of **MIL+NWFE**
NWFE+OvO-TSD		✓		investigate the effectiveness of **TSD**
LRFS+TSD	✓		✓	improve the **detection performance** with **low variability** across subjects
GrFIS+TSD	✓	✓		select the **sets of channel** for improving the **detection performance** with **low variablity** across subjects

❶ BCI Comp. III-Dataset IVa | ❷ BCI Comp. IV-Dataset 2a (4-class) | ❸ BCI Comp. IV-Dataset 2a (2-class)

Proposed Method #1 – ***NWFE+kNN+VS***

*Proposed Method #1 – **NWFE+kNN+VS***



BCI Competition III-Dataset IVa (2-class)

Channel-trial instantiation

- 5 narrow-window
- 7 statistical measure

window combination

pre-selected channel (17 channels)

kNN only

majority voting

Investigates the effectiveness of **MIL+NWFE**

NWFE+kNN+VS – Detection Performance

Experiment	Accuracy (%)					Avg.	Stdev	MAD
	aa	*al*	*av*	*aw*	*ay*			
w5	86.79	80.00	91.79	87.14	92.50	87.64	5.00	3.601
w12	93.21	95.00	95.71	96.79	97.14	95.57	1.57	1.172
w123	96.79	97.50	96.79	99.29	98.93	97.86	1.18	1.000
w1234	98.57	99.29	98.57	98.93	99.64	99.00	0.47	0.372
w12345	98.57	99.29	99.64	98.93	99.64	99.21	0.46	0.371

High Accuracy

Low Variability

Findings:

- At least 2 windows are needed to produce high accuracy and low variability
- MIL+NWFE promises to be used in EEG-MI classification

Avg. = average accuracy | Stdev = standard deviation | MAD = mean absolute deviation

NWFE+kNN+VS – Comparison to Previous Studies

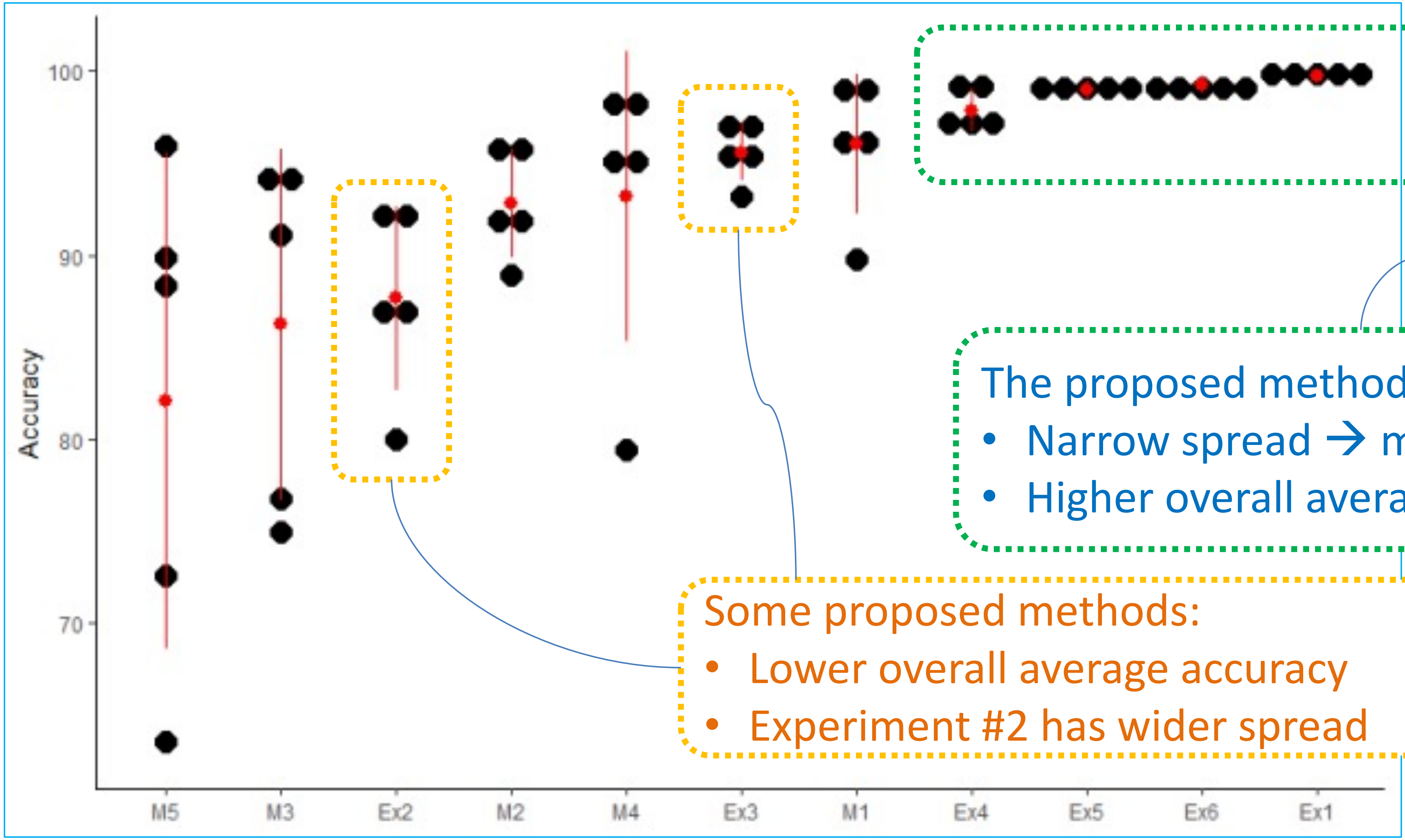
Method	Accuracy (%)*					
	aa	*al*	*av*	*aw*	*ay*	*average*
CSP+DE-FS [7]	95.8	<u>98.8</u>	<u>89.8</u>	<u>99.2</u>	<u>96.5</u>	<u>96.02 ± 3.77</u>
MSPCA+WPD+HOS [8]	<u>96</u>	92.3	88.9	95.4	91.4	92.8 ± 2.93
FBRCSP [29]	91.07	94.64	75	76.78	93.65	86.23 ± 9.55
STFSCSP [27]	95.2	98.58	79.41	97.78	95.02	92.66 ± 7.78
CSP+SF [28]	72.62	95.92	63.54	89.85	88.38	82.06 ± 13.4
Experiment #1 (w5+all-ch)	**99.64**	**99.64**	**99.64**	**99.64**	**100**	**99.71 ± 0.16**
Experiment #2 (w5+17-ch)	86.79	80.00	**91.79**	87.14	92.50	87.64 ± 5
Experiment #3 (w12+17-ch)	93.21	95.00	**95.71**	96.79	**97.14**	95.57 ± 1.57
Experiment #4 (w123+17-ch)	**96.79**	97.50	**96.79**	**99.29**	**98.93**	**97.86 ± 1.18**
Experiment #5 (w1234+17-ch)	**98.57**	**99.29**	**98.57**	**98.93**	**99.64**	**99 ± 0.47**
Experiment #6 (w12345+17-ch)	**98.57**	**99.29**	**99.64**	**98.93**	**99.64**	**99.21 ± 0.46**

more competitive results (consistent high accuracy with fewer features and channels)

Findings (vs. previous studies):

- Single window (w5) with all channels outperform previous studies
- At least 3 windows with 17 selected channels can outperform previous studies

NWFE+kNN+VS – Comparison to Previous Studies



The proposed methods mostly:

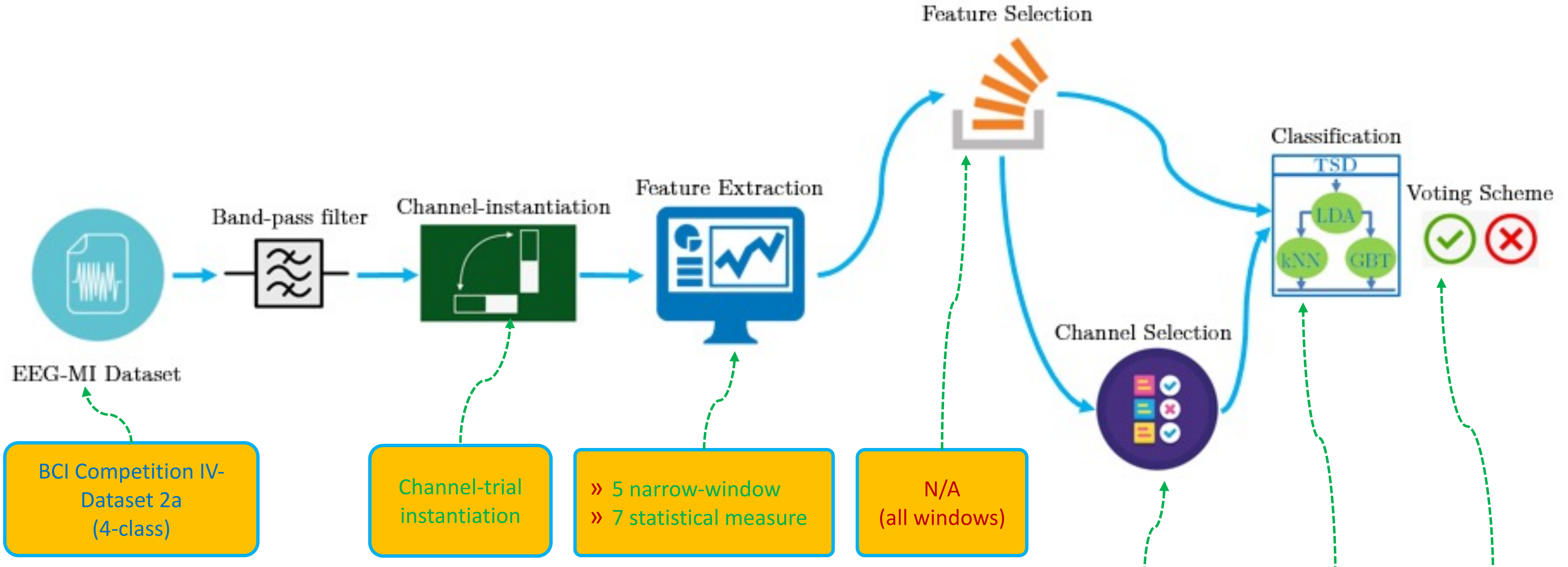
- Narrow spread → more consistent
- Higher overall average accuracy

Some proposed methods:

- Lower overall average accuracy
- Experiment #2 has wider spread

Proposed Method #2 – ***NWFE+OvO-TSD***

*Proposed Method #2 – **NWFE+OvO-TSD***



Investigates the effectiveness of

MIL + NWFE
TSD + Probability Voting

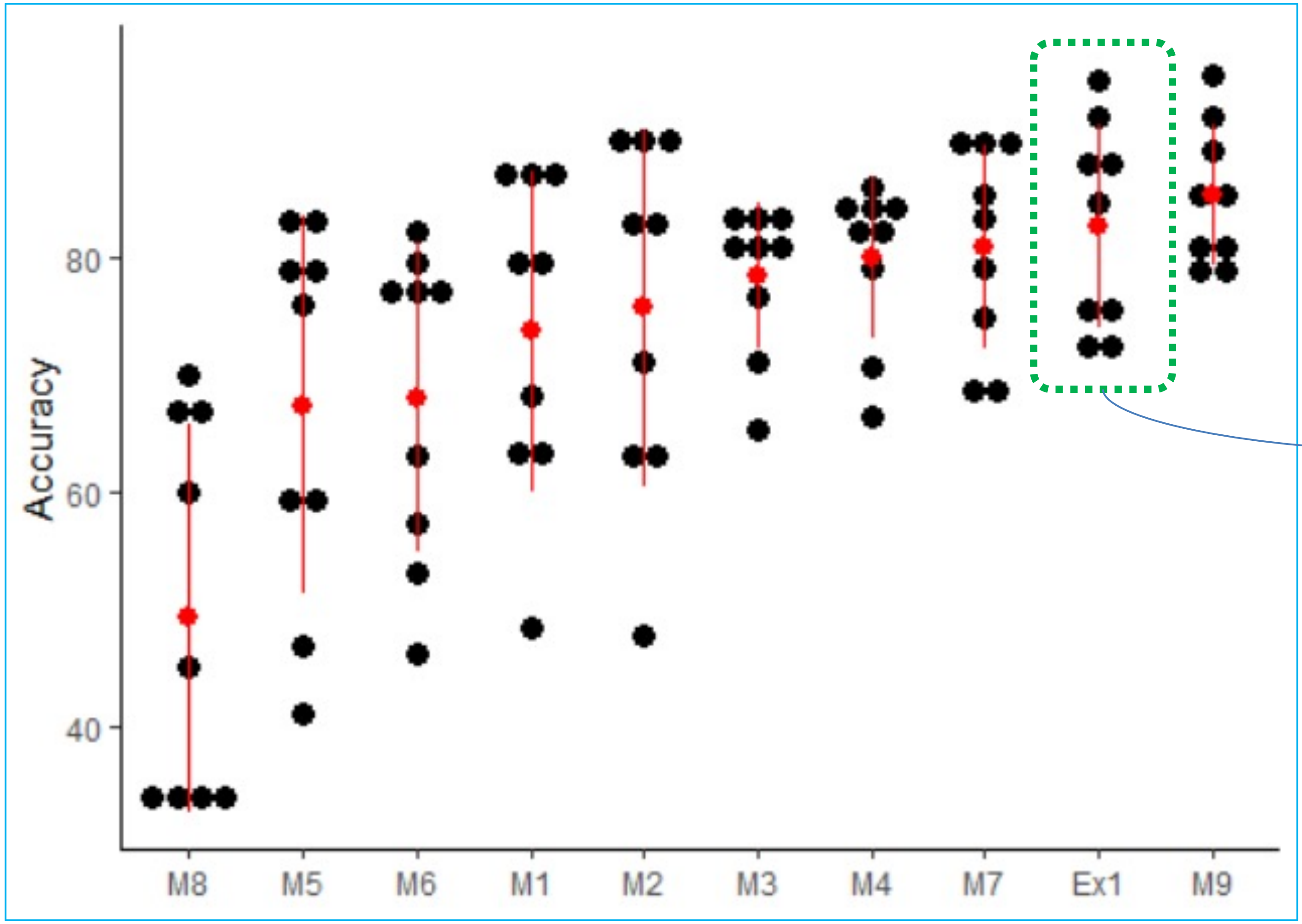
NWFE+OvO-TSD– 4-class inter-subject (accuracy)

Method	Accuracy (%)									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
CCNN [100]	87.14	63.1	86.76	68.29	63.61	48.32	87.73	80.17	78.83	73.77 ± 12.93
MCNN [100]	**90.21**	63.4	89.35	71.16	62.82	47.66	**90.86**	83.72	82.32	75.72 ± 14.37
DFBCSP+CNN Monolithic [98]	83.13	65.45	80.29	81.6	76.7	71.12	84	82.66	80.74	78.41 ± 5.91
DFBCSP+CNN Modular [98]	84.91	66.38	84.74	81.36	79.22	70.67	86.12	83.81	83.04	80.03 ± 6.52
OVO-LDA [101]	82.29	40.97	84.03	60.07	58.68	46.87	76.04	79.17	78.47	67.4 ± 15.22
OVR-LDA [101]	82.29	46.18	79.51	63.19	57.29	53.12	77.78	76.39	77.08	68.09 ± 12.56
OVO-OVR-TVT-DST [101]	83.33	69.09	88.89	79.17	75	68.06	85.42	89.24	**90.97**	81.02 ± 8.19
STR+LSC [90]	60	33	67	45	33	33	35	70	67	49.22 ± 15.60
2L-CNN [102]	85.71	78.57	**92.15**	**95.67**	**89.2**	**85.12**	79.23	81.28	80.67	**85.29 ± 5.67**
NWFE+OvO-TSD	75	**95.14**	84.72	76.04	88.19	72.92	72.22	**92.01**	87.85	82.68 ± 8.24

The proposed methods vs. Prior Research:

- Outperform 2 of 9 subjects (22.22%)
- 2nd Best for overall average accuracy

NWFE+OvO-TSD – 4-class inter-subject (accuracy)



The proposed method:

- 2nd Best
- The spread is not much different with several methods

Ex1 = NWFE+OvO-TSD

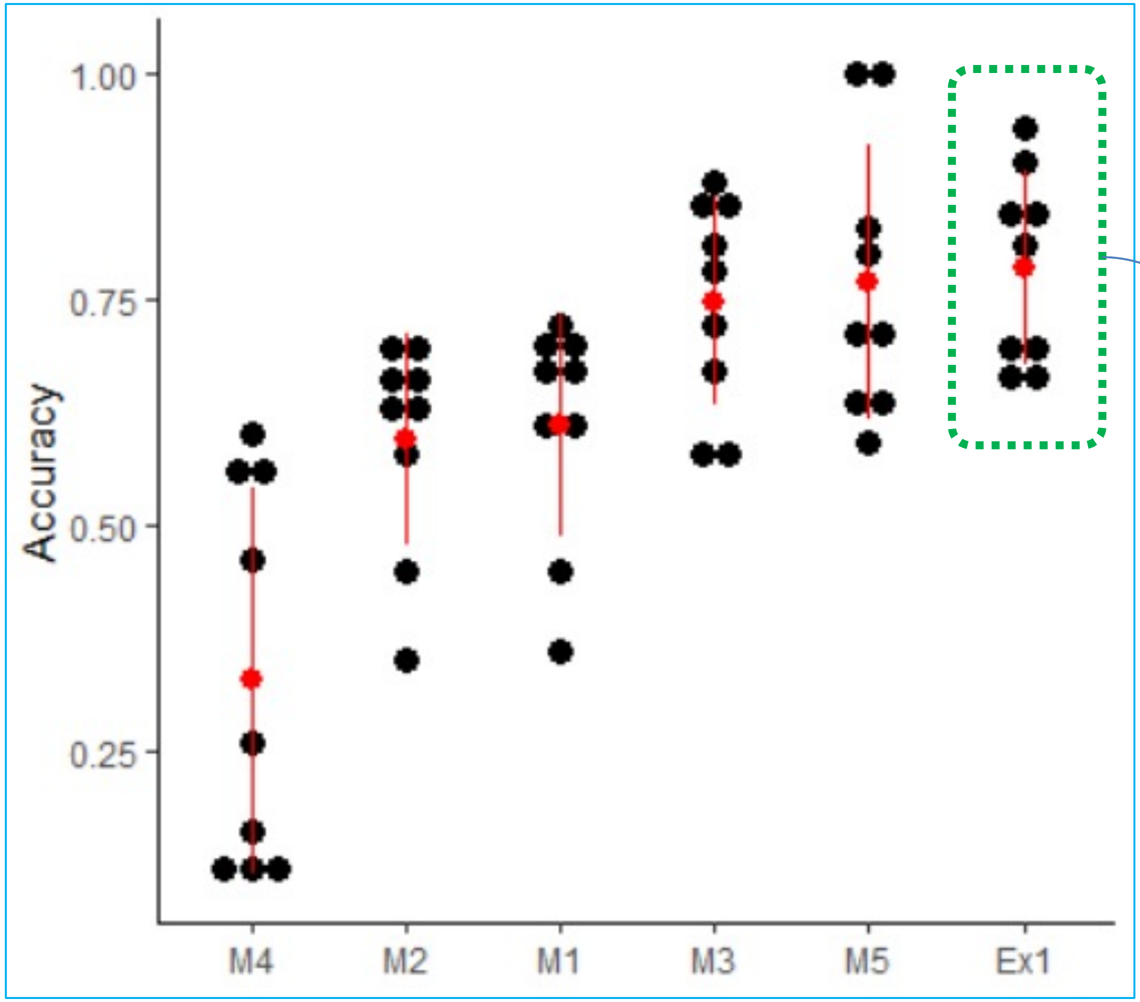
NWFE+OvO-TSD – 4-class inter-subject (kappa coeff.)

Method	Kappa coefficient									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
DFBCSP+CNN Monolithic [98]	0.68	0.36	0.69	0.62	0.6	0.45	0.71	0.72	0.66	0.61 ± 0.12
DFBCSP+CNN Modular [98]	0.67	0.35	0.65	0.62	0.58	0.45	0.69	0.7	0.64	0.59 ± 0.11
OVO-OVR-TVT-DST [101]	0.78	0.59	0.85	0.72	0.67	0.57	0.81	0.86	0.88	0.75 ± 0.11
STR+LSC [90]	0.46	0.13	0.56	0.26	0.11	0.11	0.16	0.6	0.56	0.33 ± 0.20
2L-CNN [102]	0.70	0.59	1.00	1.00	0.83	0.80	0.72	0.63	0.64	0.77 ± 0.15
NWFE+OvO-TSD	0.69	**0.94**	0.81	0.7	**0.85**	0.67	0.66	**0.9**	0.84	**0.78 ± 0.10**

The proposed methods vs. Prior Research:

- Outperform 3 of 9 subjects (33.33%)
- Higher overall average kappa coefficient + lower standard deviation

NWFE+OvO-TSD – 4-class inter-subject (kappa coeff.)



The proposed method:

- Narrow spread → more consistent
- Higher overall average kappa coefficient

Ex1 = NWFE+OvO-TSD

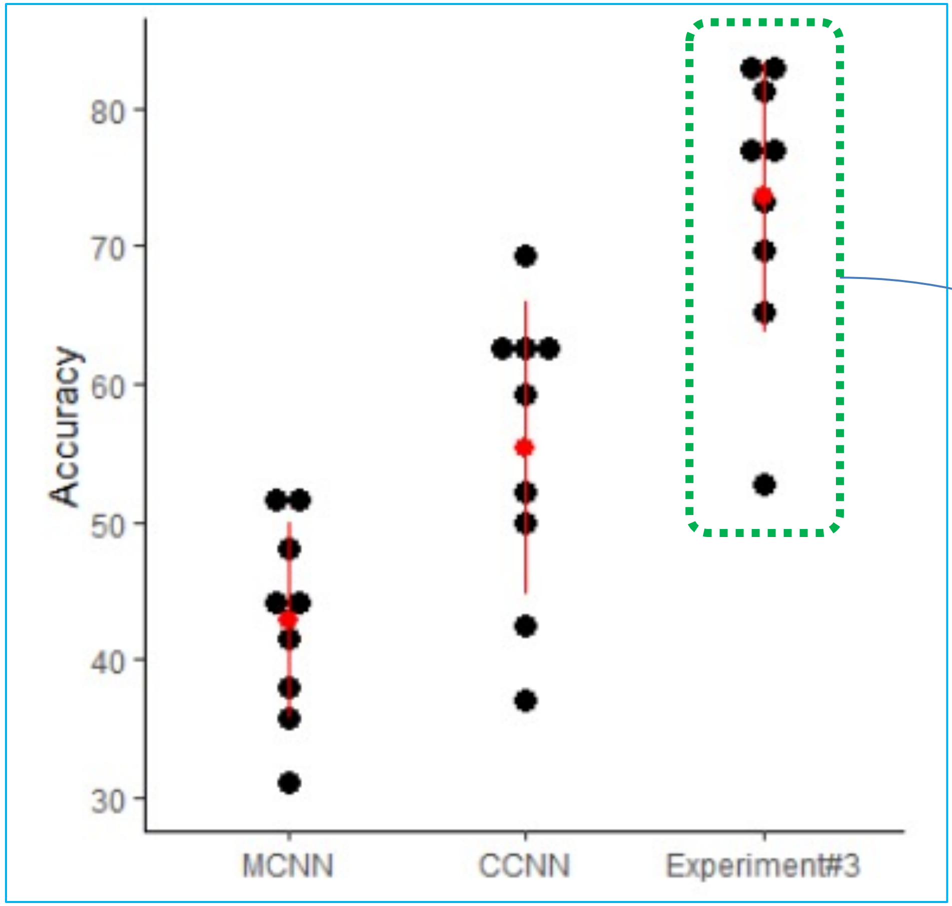
NWFE+OvO-TSD – 4-class cross-subject (accuracy)

Method	Accuracy									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
CCNN [100]	62.07	42.44	63.12	52.09	49.96	37.16	62.54	59.32	69.43	55.35 ± 10.05
MCNN [100]	51.91	38.06	43.34	35.81	41.5	31.11	48.09	45.01	51.29	42.90 ± 6.65
Experiment #3	77.43	82.99	76.39	65.28	73.26	69.79	52.78	82.99	81.25	73.57 ± 9.28

The proposed methods vs. Prior Research:

- Outperform 8 of 9 subjects (88.89%)
- Higher overall average accuracy + lower standard deviation

NWFE+OvO-TSD – 4-class cross-subject (accuracy)



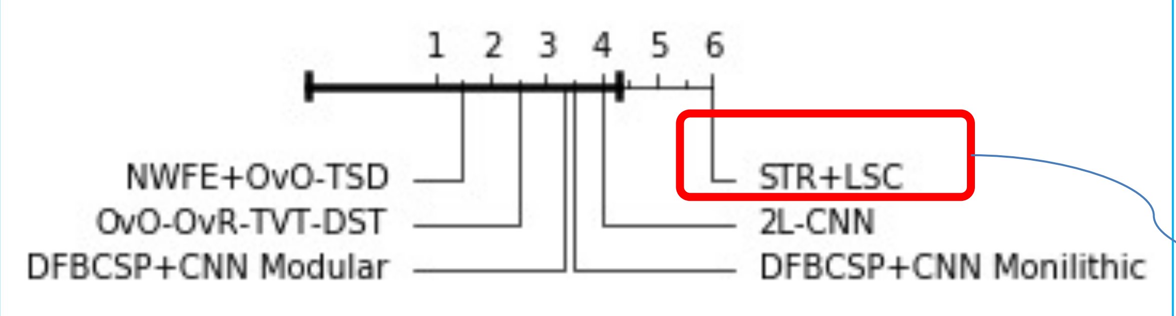
The proposed method:

- Narrow spread → more consistent
- Higher overall average accuracy

Experiment#3 = NWFE+OvO-TSD

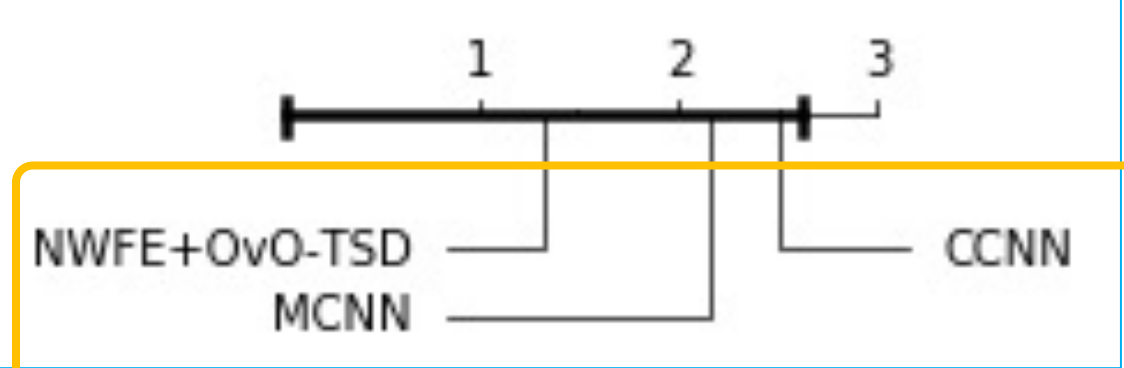
NWFE+OvO-TSD – Significance Test (Bonferonni-Dunn test)

Significant Test for inter-subject performance (CD = 2.78)



The proposed method has significant difference with one Prior Research → better and competitive

Significant Test for cross-subject performance (CD = 1.29)



The proposed method has no significant difference with Prior Research → competitive

*Proposed Method #3 – **LRFS+TSD***

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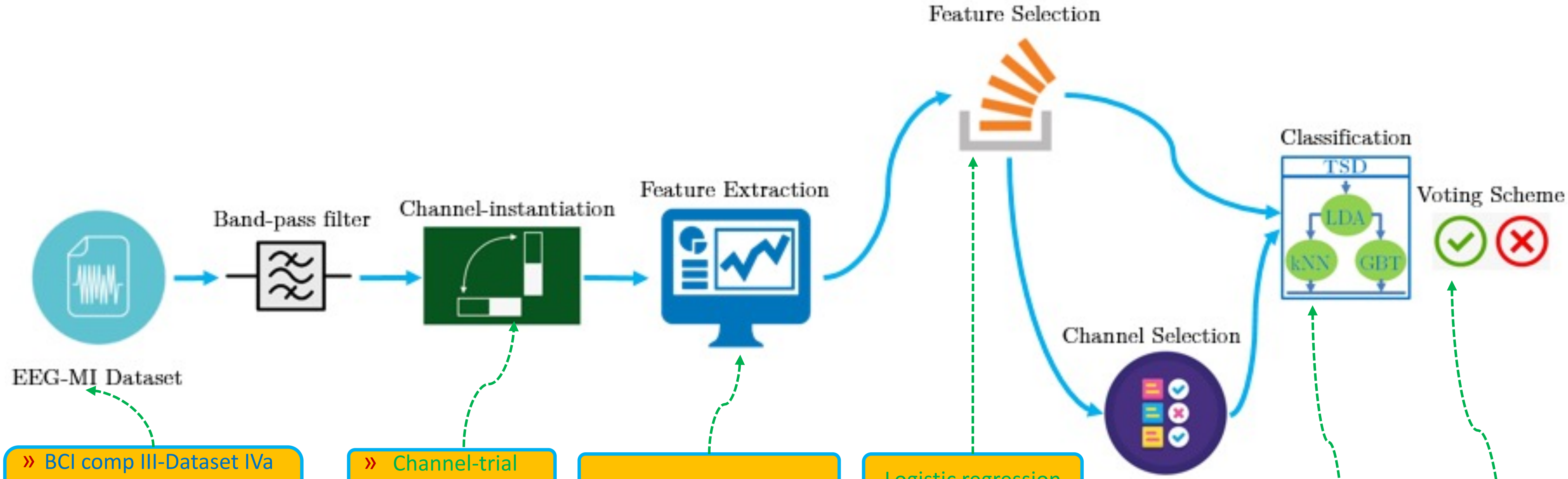


- BCI comp III-Dataset IVa (2-class)
- BCI comp IV-Dataset 2a (2-class)

- Channel-trial instantiation
- Channel-class instantiation

- 10 narrow-window
- 7 statistical measure

Logistic regression based feature selection

pre-selected channels (17 channels)

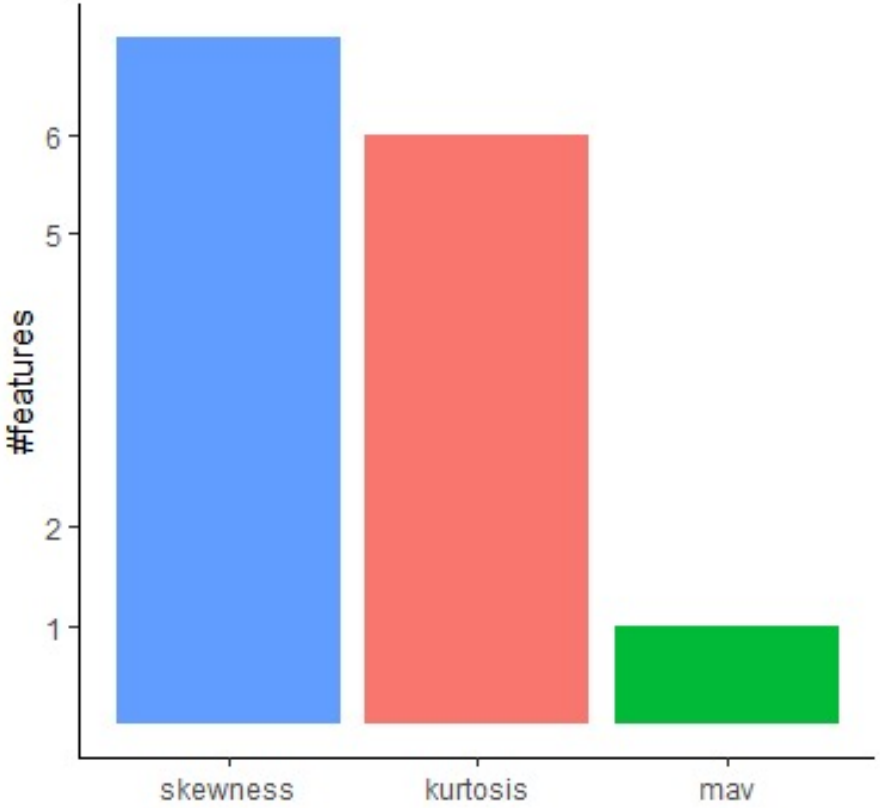
Two-stage Detection

probability voting

Improve the detection performance with low variability across subjects

LRFS+TSD – Feature Selection results

window	Selected Features	
	#Feature	Feature's Name
w1	1	skewness1
w2	3	mav2, skewness2, kurtosis2
w3	2	skewness3, kurtosis3
w4	2	skewness4, kurtosis4
w5	0	-
w6	1	skewness6
w7	1	kurtosis7
w8	1	skewness8
w9	1	kurtosis9
w10	2	skewness10, kurtosis10
Total	14	



Findings:

» skewness and kurtosis show as discriminatory features followed by mav which is also a feature that determines the effectiveness of the classification

LRFS+TSD – BCI Competition III-Dataset IVa

Method	Accuracy (%)					
	aa	al	av	aw	ay	Avg.
DSAA [84]	69.64	96.42	60.57	70.53	78.57	75.15 ± 13.49
CSP+SGRM [85]	73.9	94.5	59.5	80.7	79.9	77.70 ± 12.67
LRFCSP+SVM [86]	98.93	93.21	81.79	93.21	97.5	92.93 ± 6.73
GQCSP+SVM [89]	82.59	97.19	75.94	98.2	99	90.58 ± 10.62
CSPRMF+LDA [88]	81.43	92.41	70	83.57	85	82.48 ± 8.11
LRFS+TSD	93.93	92.14	**98.57**	**94.64**	96.79	**95.21 ± 2.51**

The proposed methods vs. Prior Research:
- Outperform 2 of 5 subjects (40%)
- Higher overall average accuracy + lower standard deviation

LRFS+TSD – BCI Competition IV-Dataset 2a (L/R only)

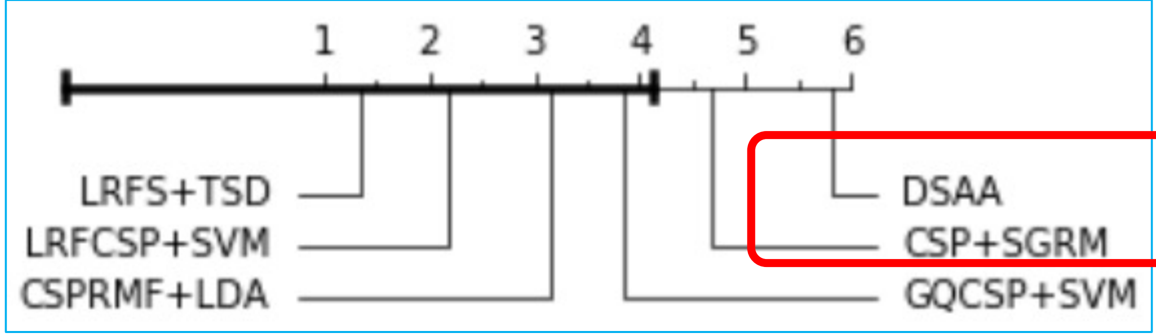
Method	Accuracy (%)									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
STR [90]	83	50	94	62	57	63	54	88	75	69.56 ± 15.93
CCSP+SVM [91]	92.1	66.7	97.3	82.8	65.5	76.9	81.8	97.4	87.5	83.11 ± 11.86
MEMDBF+CSP [92]	90.78	57.75	97.08	70.69	61.48	70.37	72.14	97.76	94.62	79.19 ± 15.85
TSGSP+SVM [93]	87	64.7	93.8	74.3	90.4	63.9	91.4	95.8	81.3	82.51 ± 12.24
ARFD+LDA [94]	74	59	83	60	60	66	67	88	90	71.89 ± 12.36
CSE+UAEL [95]	91.67	63.89	94.44	72.22	77.08	75.69	73.61	94.44	90.28	81.48 ± 11.33
DSAA [96]	88.88	80.55	93.05	52.09	87.5	90.27	92.36	85.41	92.36	84.72 ± 12.87
SJGDA+KNN [97]	90.29	74.62	93.05	75.02	75.31	78.15	85.08	92.35	94.14	84.22 ± 8.46
DFBCSP+CNN [98]	87.8	68.41	91.68	80.41	88.89	78.45	86.52	92.32	90.89	85.04 ± 7.88
LRFS+TSD	**96.53**	**97.22**	94.44	**90.97**	**100**	**95.14**	**93.06**	95.83	90.28	**94.83 ± 3.07**

The proposed methods vs. Prior Research:

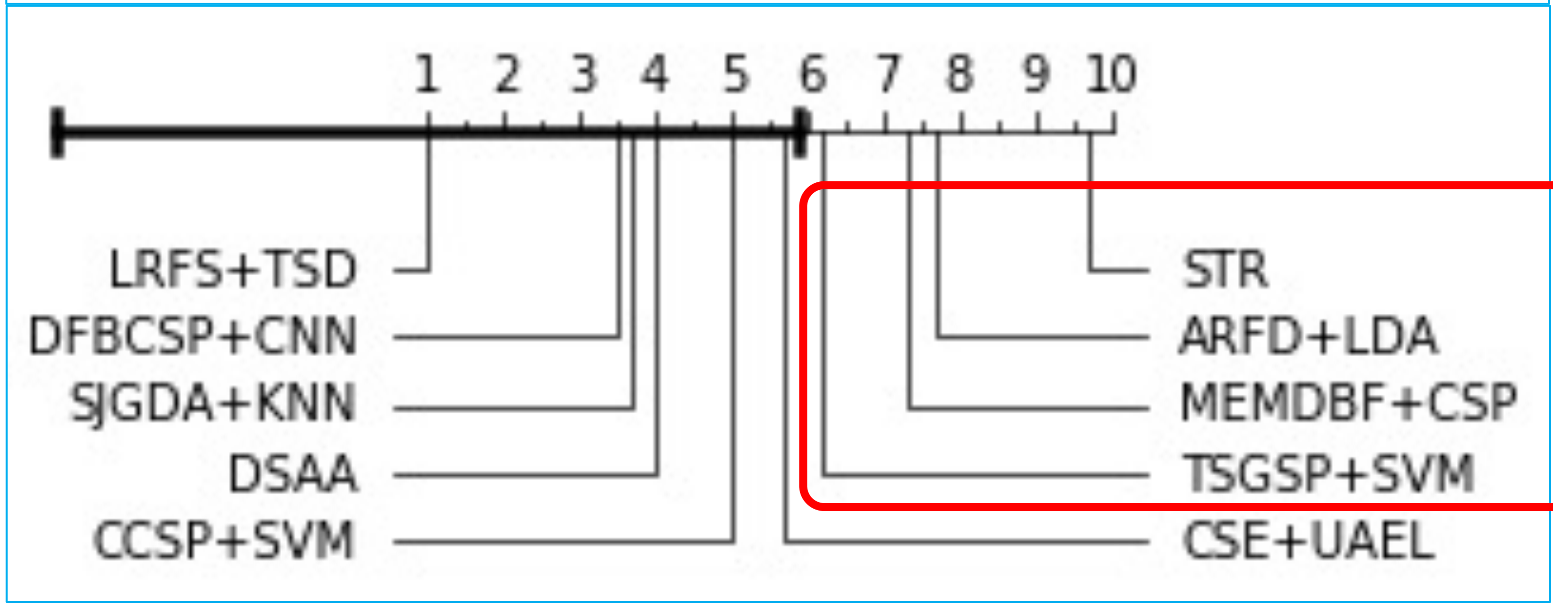
- Outperform 6 of 9 subjects (66.67%)
- Higher overall average accuracy + lower standard deviation

LRFS+TSD –Significance Test

Significant Test for BCI Comp. III-Dataset IVa (CD = 2.78)



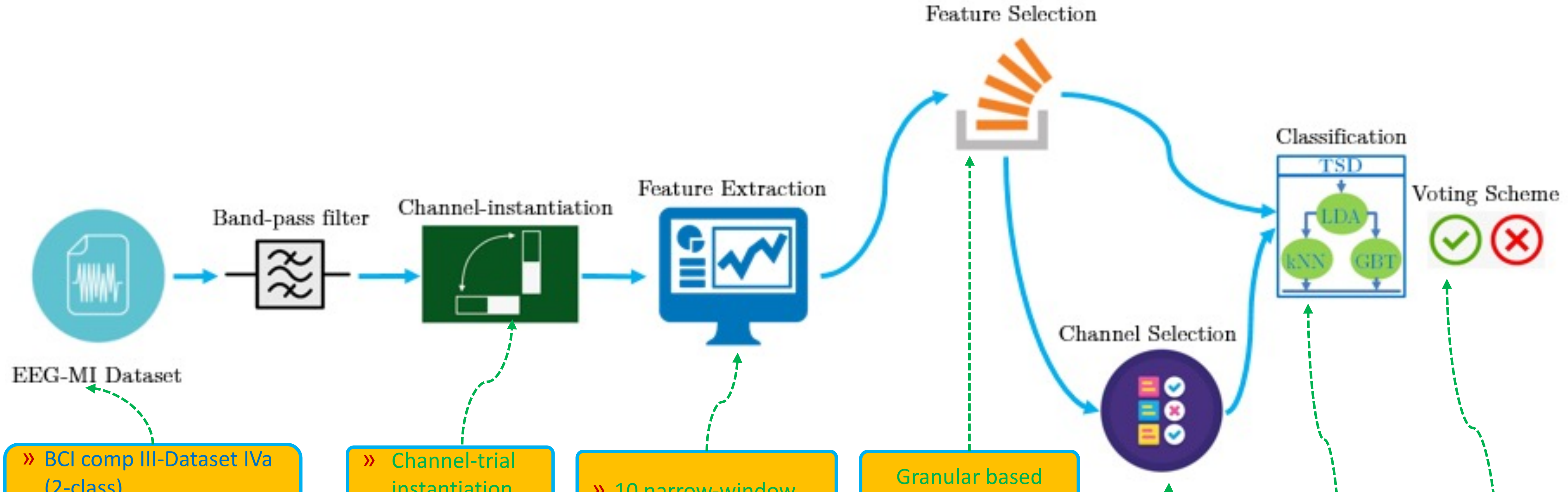
Significant Test for BCI Comp. IV-Dataset 2a (CD = 4.85)



The proposed method has significant difference with several Prior Research → better and competitive

*Proposed Method #4 – **GrFIS+TSD***

*Proposed Method #4 – **GrFIS+TSD***



- BCI comp III-Dataset IVa (2-class)
- BCI comp IV-Dataset 2a (4-class)

- Channel-trial instantiation
- Channel-class instantiation

- 10 narrow-window
- 7 statistical measure

Granular based Feature Selection (K-Means+LRFS)

Granular based Instance Selection (FCM+EN)

Two-stage Detection

probability voting

Reliable channel selection + improve detection performance with low variability across subjects

GrFIS+TSD – Channel selection results

No	ch 2a	ch IVa	#correct instance
1	EEG19	P1	248
2	EEG21	P2	247
3	Fz	Fz	245
4	EEG22	POz	245
5	EEG16	CPz	237
6	EEG17	CP2	236
7	EEG15	CP1	235
8	EEG3	FC1	234
9	EEG18	CP4	233
10	Pz	Pz	232
11	EEG4	FCz	230
12	EEG14	CP3	229
13	Cz	Cz	229
14	EEG11	C2	228
15	EEG6	FC4	224
16	EEG2	FC3	222
17	EEG9	C1	221

Top 17 selected channels:

- 17 out of 118 channels on BCI comp III-Dataset IVa
- 17 out of 22 channels on BCI comp IV-Dataset 2a

Note:

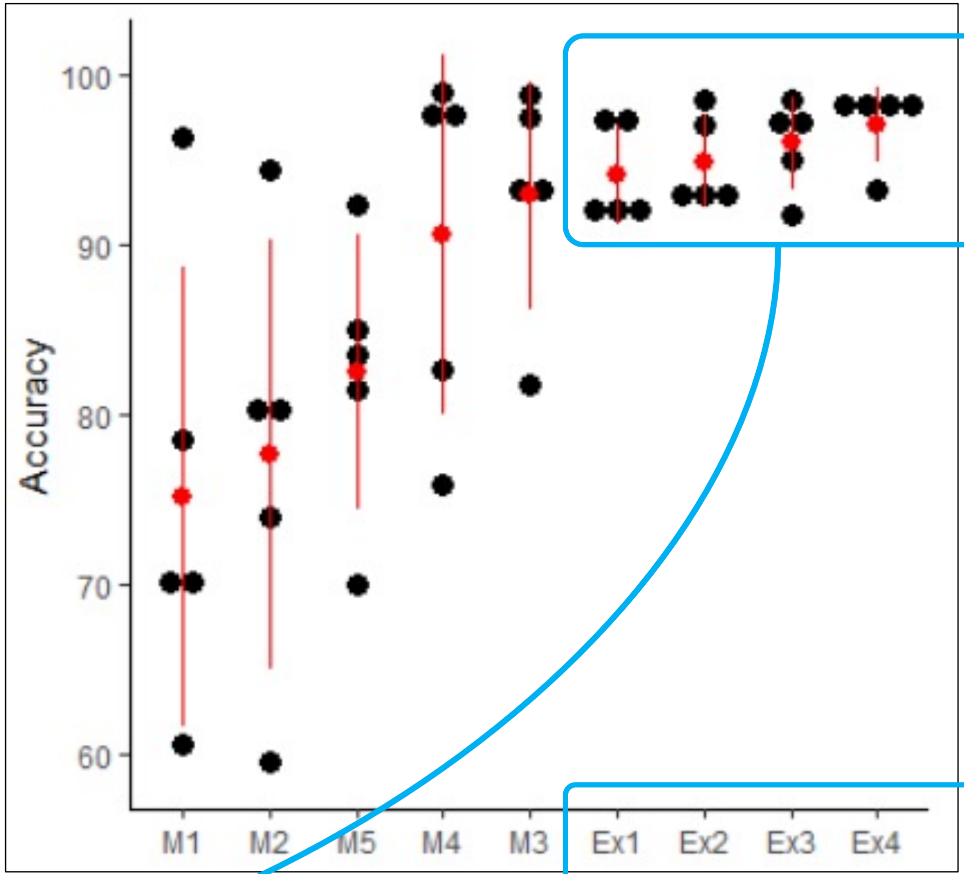
- Channel selection based in BCI comp III-Dataset IVa
- The same 17-elected channels to ensure the robustness of the Channel selection methods (GrFIS)

12 of 17 channels are related to Cortex area

Note: Top 17 channels based on granular instance selection for BCI competition III-Dataset IVa (ch IVa) and BCI competition IV-Dataset 2a (ch 2a)

GrFIS+TSD – 2-class classification

Method	Accuracy (%)					
	aa	al	av	aw	ay	Avg.
DSAA [107]	69.64	96.42	60.57	70.53	78.57	75.15 ± 13.49
CSP+SGRM [67]	73.9	94.5	59.5	80.7	79.9	77.70 ± 12.67
LRFCSP+SVM [70]	**98.93**	93.21	81.79	93.21	97.5	92.93 ± 6.73
GQCSP+SVM [105]	82.59	**97.19**	75.94	**98.2**	**99**	90.58 ± 10.62
CSPRMF+LDA [72]	81.43	92.41	70	83.57	85	82.48 ± 8.11
Experiment #1 (11-ch)	97.86	91.79	**92.50**	96.79	91.79	**94.15 ± 2.63**
Experiment #2 (13-ch)	98.57	92.86	**92.50**	97.14	93.57	**94.93 ± 2.46**
Experiment #3 (15-ch)	97.50	91.79	**95.00**	97.14	98.57	**96.00 ± 2.40**
Experiment #4 (17-ch)	97.86	93.21	**98.21**	97.86	98.57	**97.14 ± 1.98**



Findings:

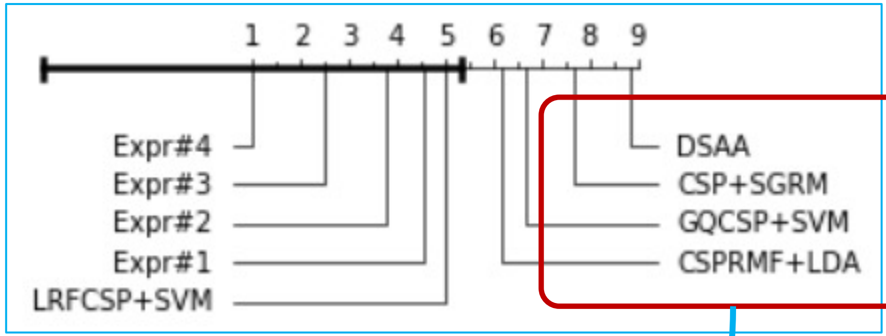
» all experiments **outperformed** the previous studies in both average accuracy and standard deviation

» higher average accuracy → **improve the detection**

» narrower spread → **low variability**

GrFIS+TSD – Significance test

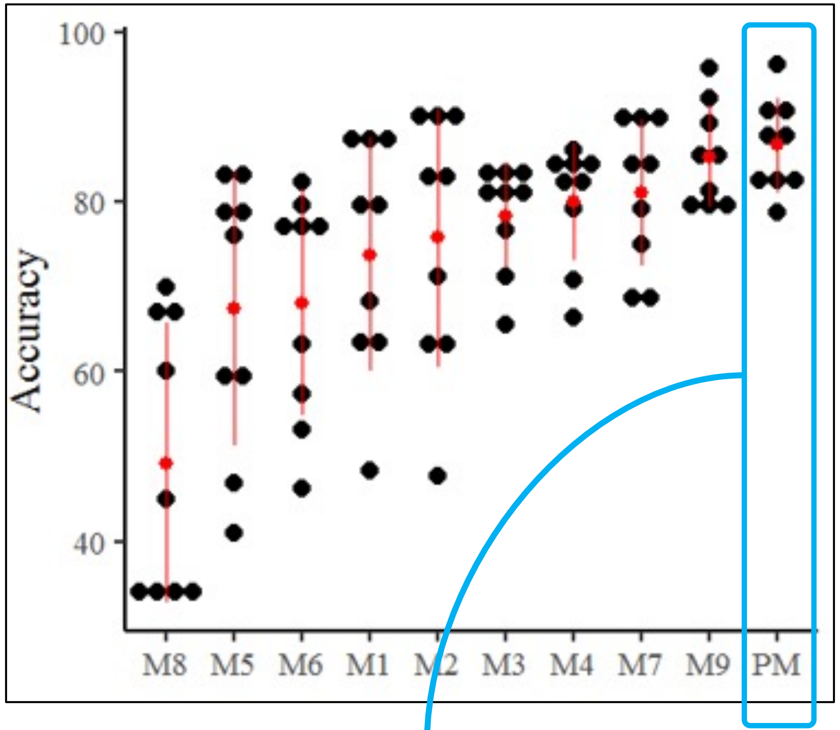
Method	Rank						Avg. Rank
	Range	Q1	Q3	MAD	CV	CVQ	
DSAA [107]	9	9	9	9	9	8	8.83
CSP+SGRM [67]	8	8	8	7	8	7	7.67
LRFCSP+SVM [70]	5	3	3	5	5	4	4.17
GQCSP+SVM [105]	7	6	2	8	7	9	6.50
CSPRMF+LDA [72]	6	7	7	6	6	3	5.83
Experiment #1 (7-ch)	2.5	5	6	4	4	6	4.58
Experiment #2 (9-ch)	2.5	4	5	3	3	5	3.75
Experiment #3 (11-ch)	4	2	3	2	2	2	2.50
Experiment #4 (13-ch)	1	1	1	1	1	1	1.00



Findings:
- 3 out of 4 experiments **ranked lower** than the previous studies
- all experiments have **significant differences** with most of the previous studies

GrFIS+TSD – 4-class classification (accuracy)

Method	Accuracy (%)									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
CCNN [106]	87.14	63.1	86.76	68.29	63.61	48.32	87.73	80.17	78.83	73.77 ± 12.93
MCNN [106]	**90.21**	63.4	89.35	71.16	62.82	47.66	**90.86**	83.72	82.32	75.72 ± 14.37
DFBCSP+CNN Monolithic [69]	83.13	65.45	80.29	81.6	76.7	71.12	84	82.66	80.74	78.41 ± 5.91
DFBCSP+CNN Modular [69]	84.91	66.38	84.74	81.36	79.22	70.67	86.12	83.81	83.04	80.03 ± 6.52
OVO-LDA [65]	82.29	40.97	84.03	60.07	58.68	46.87	76.04	79.17	78.47	67.4 ± 15.22
OVR-LDA [65]	82.29	46.18	79.51	63.19	57.29	53.12	77.78	76.39	77.08	68.09 ± 12.56
OVO-OVR-TVT-DST [65]	83.33	69.09	88.89	79.17	75	68.06	85.42	89.24	**90.97**	81.02 ± 8.19
STR+LSC [78]	60	33	67	45	33	33	35	70	67	49.22 ± 15.60
2L-CNN [121]	85.71	78.57	**92.15**	**95.67**	89.2	**85.12**	79.23	81.28	80.67	85.29 ± 5.67
GrFIS+TSD	86.81	**96.18**	88.54	81.6	**91.67**	83.33	78.82	**89.58**	82.99	**86.61 ± 5.16**

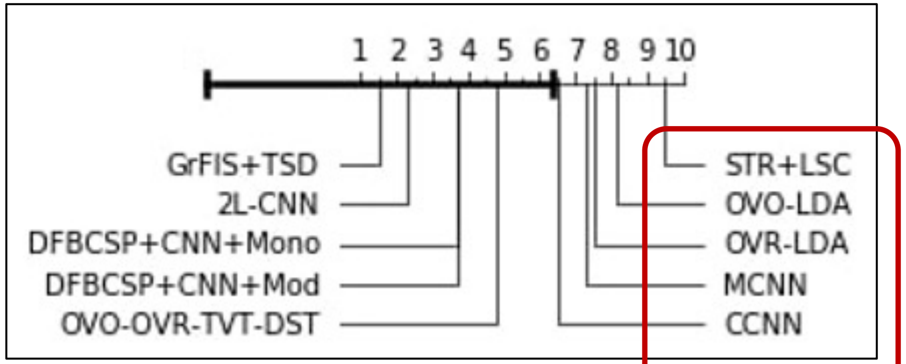


narrower spread → **lower variability**

higher average accuracy → **improve the detection**

GrFIS+TSD – Significance test

Method	Rank						Avg. Rank
	Range	Q1	Q3	MAD	CV	CVQ	
CCNN [106]	8	6	5	6	6	8	6.50
MCNN [106]	10	7	2	8	8	9	7.33
DFBCSP+CNN Monolithic [69]	3	4	7	3	3	2	3.67
DFBCSP+CNN Modular [69]	4	3	6	4	4	1	3.67
OVO-LDA [65]	9	8	8	9	9	6	8.17
OVR-LDA [65]	6	9	9	7	7	7	7.50
OVO-OVR-TVT-DST [65]	5	5	4	5	5	5	4.83
STR+LSC [78]	7	10	10	10	10	10	9.50
2L-CNN [121]	1	2	3	2	2	4	2.33
GrFIS+TSD	2	1	1	1	1	3	1.50



Findings:

» the proposed method has the **lower number of rank** compared to the previous studies

» the proposed method has **significant differences** with most of the previous studies

*5. Comparison **between** The Proposed Methods*

Comparison **between The Proposed Methods**

BCI competition III – Dataset IVa (2-class)

Method	Experiment	Accuracy (%)					Average
		aa	*al*	*av*	*aw*	*ay*	
NWFE+kNN+VS	14 F + 17-ch	93.21	95.00	95.71	96.79	97.14	95.57 ± 1.57
	21 F + 17-ch	96.79	97.50	96.79	99.29	98.93	97.86 ± 1.18
LRFS+TSD	14 F + 17-ch	93.93	92.14	98.57	94.64	96.79	95.21 ± 2.51
GrFIS+TSD	19 F + 17-ch	97.86	93.21	98.21	97.86	98.57	97.14 ± 1.98

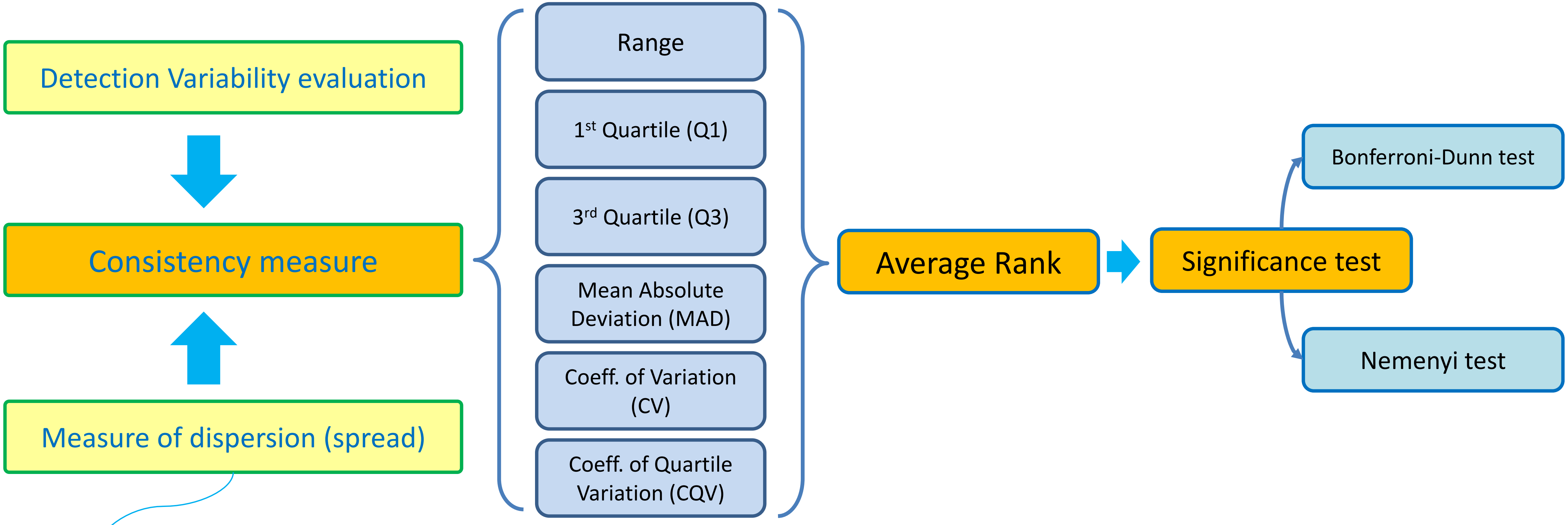
BCI competition IV – Dataset 2a (4-class)

Method	Accuracy (%)									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
NWFE+OvO-TSD	75	95.14	84.72	76.04	88.19	72.92	72.22	92.01	87.85	82.68 ± 8.24
GrFIS+TSD	86.81	96.18	88.54	81.6	91.67	83.33	78.82	89.58	82.99	86.61 ± 5.16

GrFIS+TSD show its ***effectiveness*** and ***competitiveness***

*6. Discussion – **Consistency** Measure and **Rationalization** of Improvement*

Consistency *Measure*



» measures of dispersion is a measure used to show how spread out (variation) in a data set (Mishra et al., 2019)
» measure of dispersion indicates the degree of spread or distribution of the data (Sheard, 2018)
» ...also called measures of variation (Mishra et al., 2019)
» ...also expressed by fluctuation, spread, scatter, or variation (Rayat, 2018)

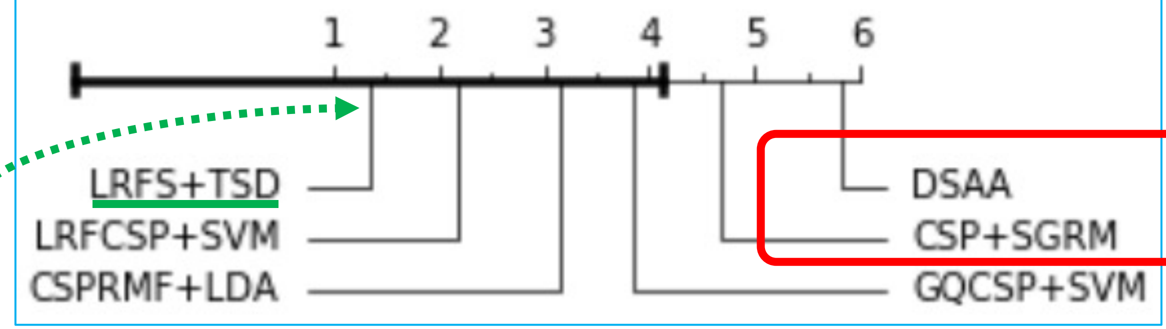
Consistency *Measure – Example from The Proposed Method #3 (LRFS+TSD)*

Method	Accuracy (%)*				
	aa	*al*	*av*	*aw*	*ay*
DSAA [88]	69.64	96.42	60.57	70.53	78.57
CSP+SGRM [89]	73.9	94.5	59.5	80.7	79.9
LRFCSP+SVM [90]	98.93	93.21	81.79	93.21	97.5
GQCSP+SVM [91]	82.59	97.19	75.94	98.2	99
CSPRMF+LDA [92]	81.43	92.41	70	83.57	85
LRFS+TSD (17-ch)	93.93	92.14	98.57	94.64	96.79

Methods	Range	Q1	Q3	MAD	CV	CQV
DSAA [88]	35.85	69.64	78.57	9.8792	0.1796	0.0603
CSP+SGRM [89]	35	73.9	80.7	8.8000	0.1630	0.0440
LRFCSP+SVM [90]	17.14	93.21	97.5	4.4552	0.0724	0.0225
GQCSP+SVM [91]	23.06	82.59	98.2	9.0552	0.1172	0.0863
CSPRMF+LDA [92]	22.41	81.43	85	5.4136	0.0983	0.0215
LRFS+TSD (17-ch)	6.43	93.93	96.79	1.9728	0.0263	0.0150

Methods	Range	Q1	Q3	MAD	CV	CQV	Avg. Rank
DSAA [88]	6	6	6	6	6	5	5.83
CSP+SGRM [89]	5	5	5	4	5	4	4.67
LRFCSP+SVM [90]	2	2	2	2	2	3	2.17
GQCSP+SVM [91]	4	3	1	5	4	6	3.83
CSPRMF+LDA [92]	3	4	4	3	3	2	3.17
LRFS+TSD (17-ch)	1	1	3	1	1	1	1.33

Significant Test for BCI Comp. III-Dataset IVa (CD = 2.78)



More consistent compared to all previous studies

Rationalization *of Improvement*

1. Feature Extraction Technique
   - Narrow Windows Approach → *handling non-stationary EEG signal*
   - Statistical Features → *7 statistical measures (5 SoTA, 2 new implementation)*
2. Feature-Channel Selection Technique
   - Granular Computing Approach → *clustering based granulation*
3. Classifier Approach
   - Ensemble Technique → *hybrid classifier*
4. Learning Approach
   - Multi-instance Learning Approach → *instance-level*
   - Voting Scheme → *majority voting and probability voting*

7. Conclusions and Future Works

Conclusions

- A combination of multi-instance learning, narrow window feature extraction, and ensemble learning approaches is *able to address subject-dependent problems* effectively, and the results are promising

- The granular computing approach has demonstrated its *efficacy for feature selection and channel selection* by producing competitive and robust results for a wide range of subjects across many datasets.

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That’s all, thank you…

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