生物与医学工程学院
BUAA SCHOOL OF BIOLOGICAL SCIENCE AND MEDICAL ENGINEERING

A Comparative Study on EEG-based Models for Automatic Discrimination of Mental Attentional Levels during Simulated Flying Tasks

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- **Objectives and design**
- **Significance**
- **Methods**
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- **Conclusion**
- **Discussion**

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Background

- **Monitoring attentional level of pilots can reduce the number of accidents caused by low attentional level during flying**

Background

Study	Application background	EEG channels	preprocessing	Feature extracted	classifier	Offline/Online	fps	acc
Huan Wu, 2020	-	4	Wavelet transform	β/θ, SE	/	Offline	NA	/
Wei,2018	Driving alertness/fatigue	4*	Bandpass filtering, artifact elimination	Features of α, β, θ band	LDA, kNN, SVM	Offline	NA	0.781, 0.773, 0.8
Hu,2018	Driving alertness/fatigue	30*	Bandpass filtering	SE	GBDT	Offline	NA	0.94
HaiYu Wang,2018	Driving alertness/fatigue	30*	Wavelet transform	Principle components of α/β/θ/δ band features	LS-SVM	Offline	NA	0.8947
Koji,2017	Identification of road signs	1	Baseline correction, threshold rejection (±80μV)	Features of θ band	DCNN	Offline	NA	/
Monammad, 2018	Driving alertness/fatigue	4*	None (Raw data)	/	deep CNN	Offline	NA	0.9531
Wang, 2018	Driving alertness/fatigue	24	Detrending, baseline correction, bandpass filtering	PSD SE	/	Online	0.1fps(10s sequence) 0.5fps(2s sequence)	/
Costa, 2019	Attentional level during rehabilitation training	31*	Bandpass filtering, standardization, Maximum entropy spectrum estimation	Features of γ band	LDA	Online	1fps(1s sequence)	0.681

Note: '*' represents 32-channel EEG

Background

Remaining problems

1. **Low accuracy in online (real-time) classification**
2. **Low versatility when models are applied to multiple subjects**
3. **Few comparative studies on the performances of different attentional level detection models**

Contents

Objectives and design

Objective

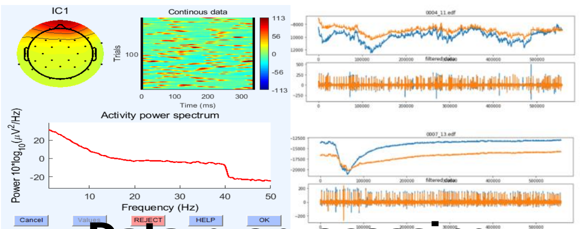
- **Discriminate different attentional levels (L/M/H) during simulated flying tasks (0.5 fps: 2s sequence for classification)**
- **Compare the performances of 1) classic classifiers and 2) deep learning models in terms of their accuracy and versatility**

Objectives and design

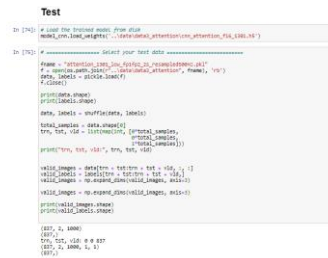
Data collection

Attentional level	Task difficulty	Main task
L	L	Watch recorded flying tasks
M	M	Perform simulated flying tasks
H	H	Perform simulated flying tasks with constraints

Objectives and design

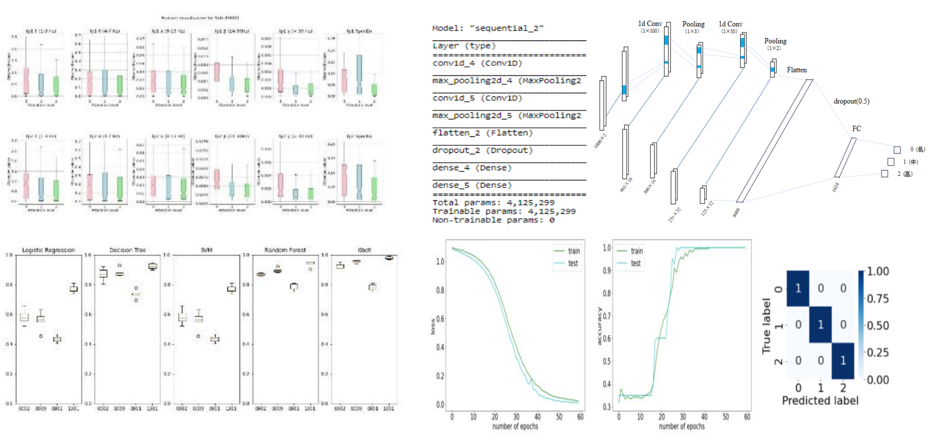


Data preprocessing and quality control

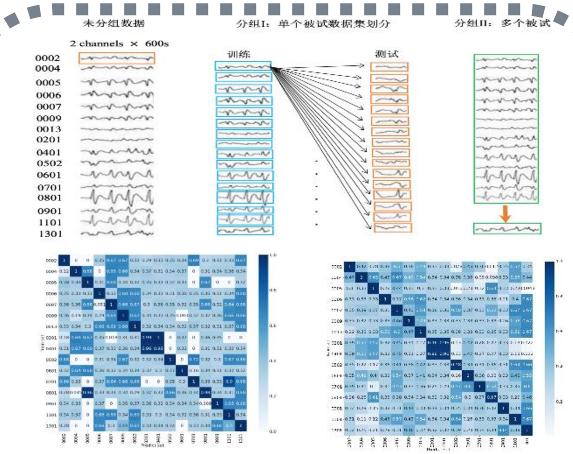


被试	LR	Tree	svm	RF	Gbdt	CNN
0002	0.412186	0.335723	0.379928	0.332139	0.336918	0.333
0004	0.307416	0.246411	0.349282	0.312201	0.312201	0.359
0005	0.251196	0.358852	0.348086	0.385167	0.368421	0.305
0006	0.363202	0.410992	0.400239	0.42055	0.359618	0.468
0007	0.421744	0.448029	0.44325	0.540024	0.630824	0.427
0009	0.289128	0.335723	0.483871	0.422939	0.464755	0.538
0013	0.414576	0.620072	0.462366	0.694146	0.615293	0.594
0201	0.387136	1	0.485437	1	0.580097	0.472
0401	0.387136	1	0.485437	1	0.580097	0.802
0502	0.439665	0.126643	0.396655	0.131422	0.317802	0.329
0601	0.51976	0.512575	0.335329	0.513772	0.500599	0.323
0701	0.372455	0.267066	0.353293	0.354491	0.346108	0.333
0801	0.410778	0.348503	0.449102	0.337725	0.495808	0.598
0901	0.345281	0.426523	0.34767	0.452808	0.339307	0.667
1101	0.517324	0.388292	0.37276	0.555556	0.593787	0.609
1301	0.401434	0.467145	0.473118	0.51374	0.574671	0.99
AVG±SD	0.39±0.07	0.46±0.24	0.41±0.06	0.50±0.23	0.46±0.12	0.51±0.20

On one single subject



Exploratory analysis, visualization, building and testing models on a baseline dataset



On multiple subjects

Contents

Significance

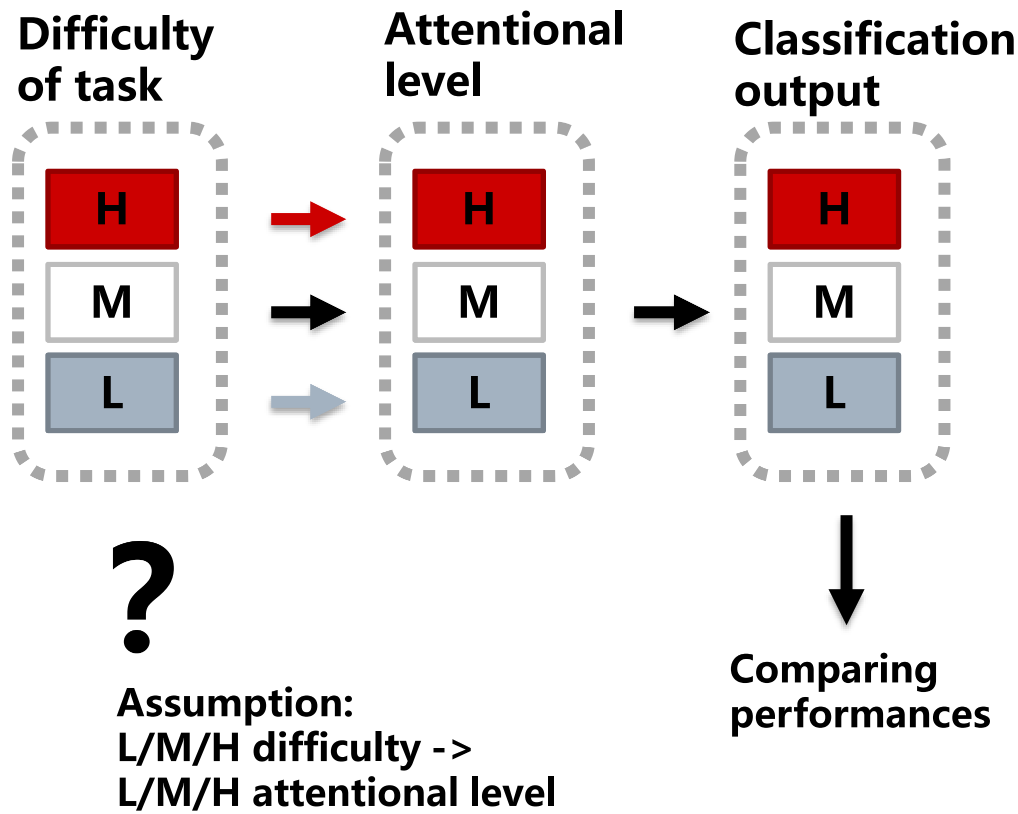
- **From an application perspective,**
  - **Help avoid accidents caused by decreased attention level during long-term tasks**
- **From a research perspective,**
  - **By comparing the performances of different models, this study will provide information to help select and optimize real-time attentional level detection methods.**

Contents

Methods

Data collection

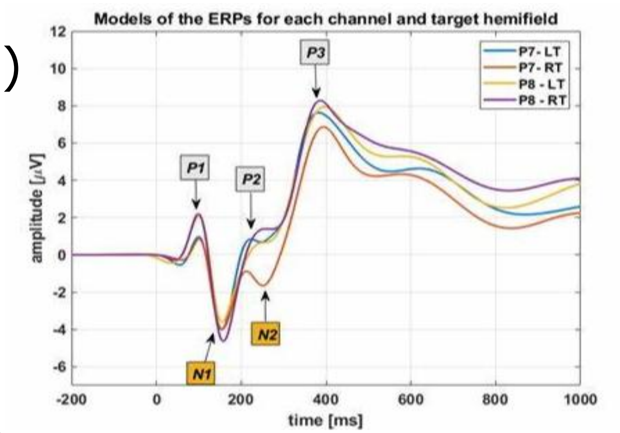
Attentional level	Task difficulty	Main task
L	L	Watch recorded flying tasks
M	M	Perform simulated flying tasks
H	H	Perform simulated flying tasks with constraints



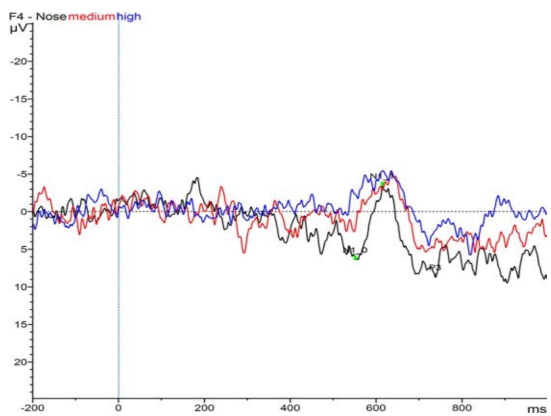
Methods

Secondary task (auditory stimulus)

(a)



(c)



While performing the main task at L->M->H difficulty:

- **Smaller changes in amplitude of N1 and P3 caused by auditory stimulus**
- **Less attentional resource for secondary task**
- **Higher attentional level for the main task**

(b)

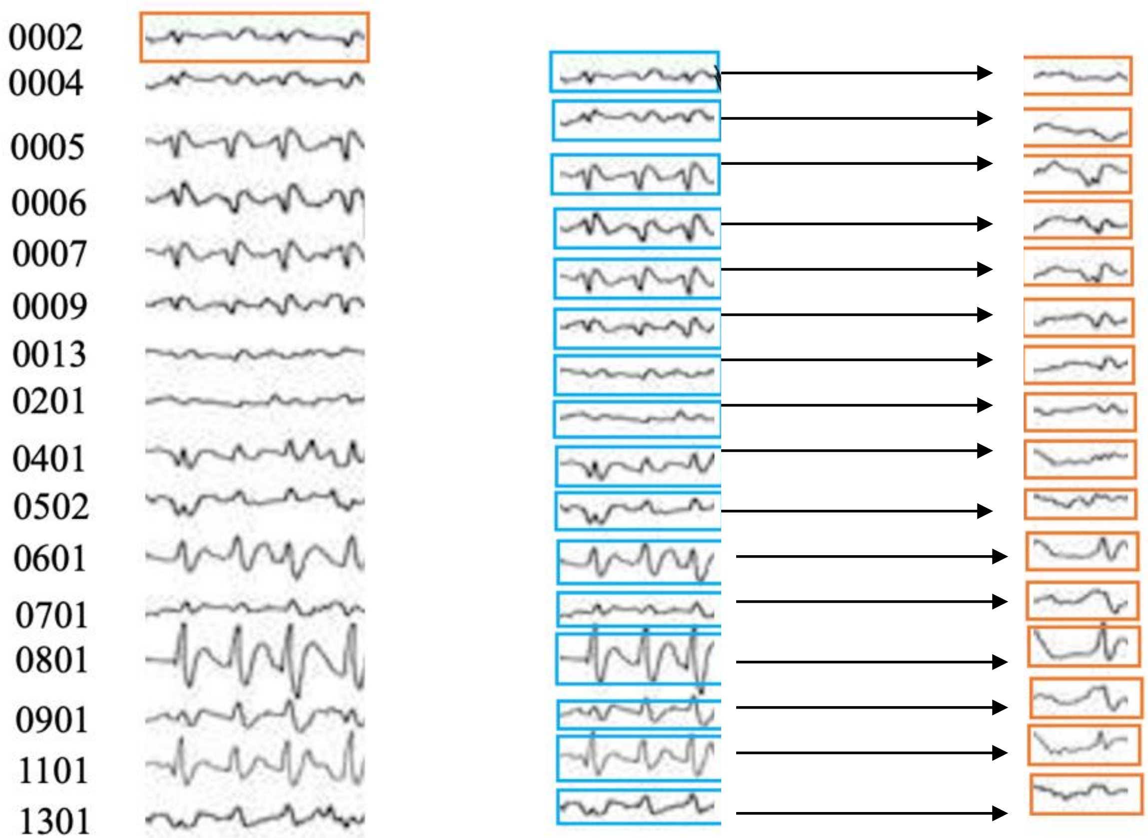
N1	F4	F7	F8
L	-9.83487	-9.07869	-11.6394
M	-7.94818	-6.68929	-9.08544
H	-5.98145	-5.6432	-7.30027

P3	Fz	F7	F3	FC1	FC2
L	11.17331	12.05532	10.08901	11.85864	12.46203
M	10.55667	8.036693	8.90429	10.75337	11.39706
H	8.866953	4.57331	6.886431	9.285172	10.12889

Methods

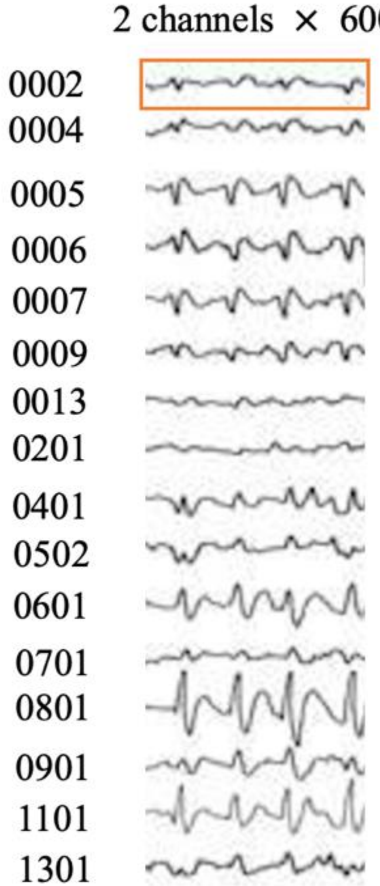
Data not grouped
(16 subjects)
2 channels × 600s

Grouping 1 (single subject test):
Train on subject A + Test on subject A

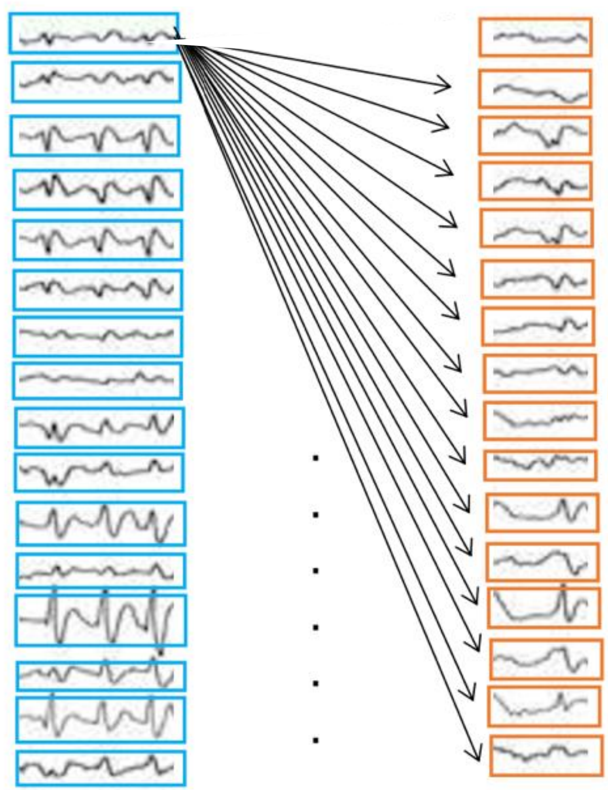


Methods

Data not grouped
(16 subjects)

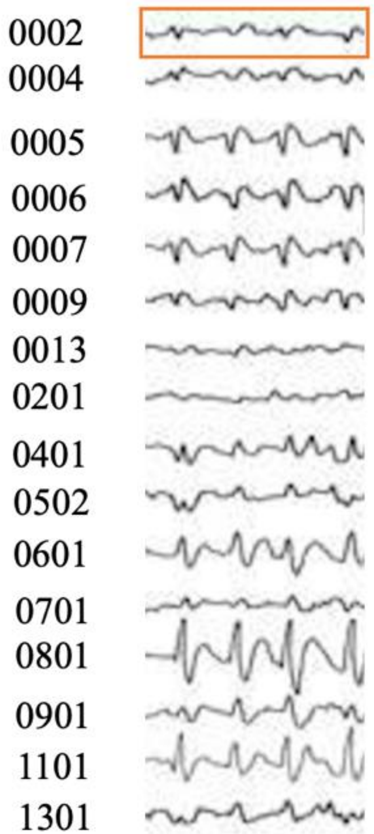


Grouping 2 (single subject cross test):
Train on subject A + Test on subject B

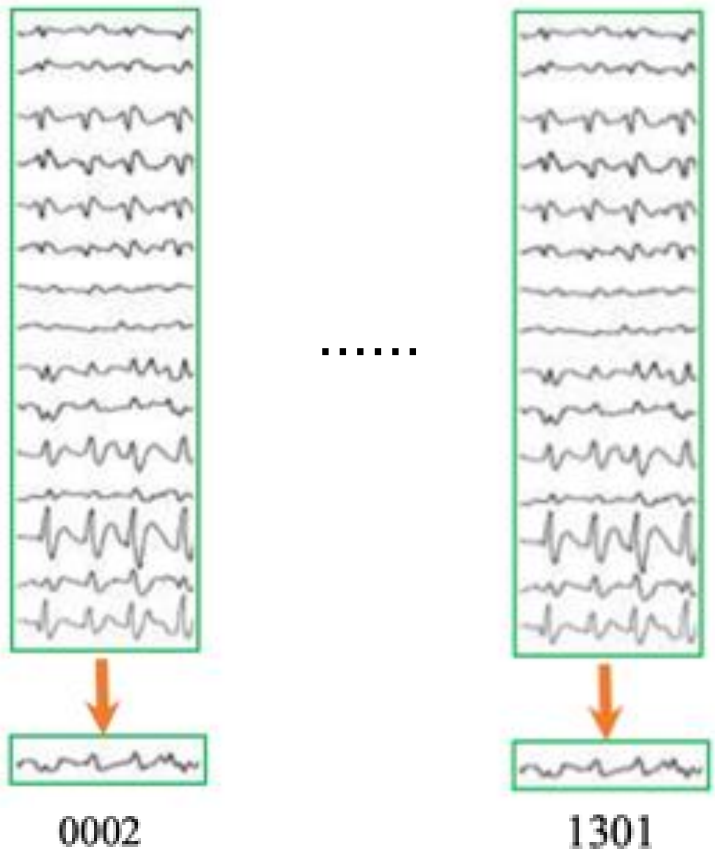


Methods

Data not grouped
(16 subjects)
2 channels × 600s



Grouping 3 (multiple subjects cross test):
Train on 15 subjects other than A + Test on subject A



Methods

Experiment setup

- **EEGLAB 14_1_2b**
- **Python 3.8.3 (conda 4.9.2，jupyter 1.0.0，notebook 6.1.5，keras 2.4.3，numpy 1.19.4，pandas 1.1.5，scikit-learn 0.23.2，scipy 1.5.3，tensorflow 2.3.0，mne 0.22.0，matplotlib 3.3.3，seaborn 0.11.0)**
- **1×Intel(R) Core i7-8550U CPU，1×Intel(TM) Core i5-4300U CPU。**

Contents

Testing on a baseline dataset with the expected input dimensions for rationality check

Pre-experiment

- **Preparing baseline dataset**
- **Testing classic classification models**
- **Testing and tuning DL models**

Experiment

- **Data preparation**
- **Model effectiveness: single subject test**
- **Model versatility: single subject / multiple subjects cross test**

Pre-experiment

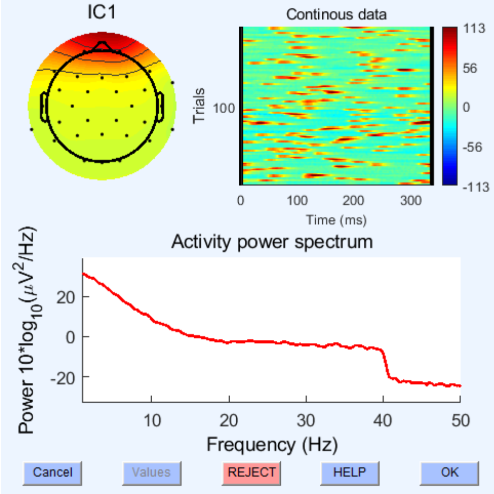
Baseline dataset

- **Strictly controlled data quality**
- **Relatively consistent data distribution**
- **Less randomness**
- **Separable (for classification, with learnable features)**

Pre-experiment

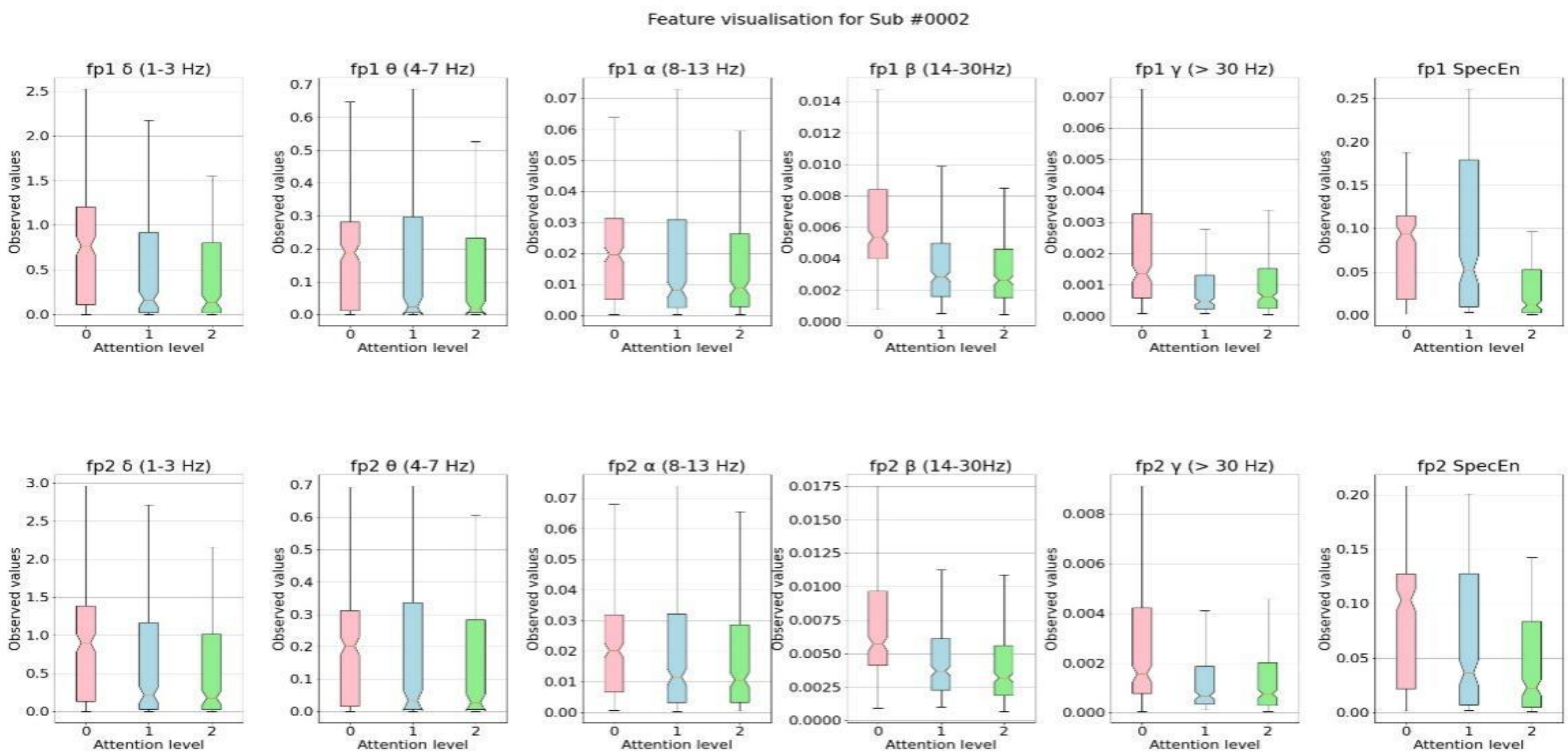
Preparing baseline dataset: manual pre-processing

- **EEG data of subject 0002, 0009, 0801, 1301**
- **Import .edf file**
- **Electrode placement: 10-5 system**
- **Remove VEOG、HEOG、ECG**
- **Re-reference on Fc6**
- **Resample to 500Hz**
- **Bandpass filtering 0.1-40Hz**
- **Baseline correction, interpolating, rejecting bad segments**
- **ICA**
- **Take Fp1，Fp2 channels, divide into 2s sequences (2 channels×1000 sample points)**



Pre-experiment

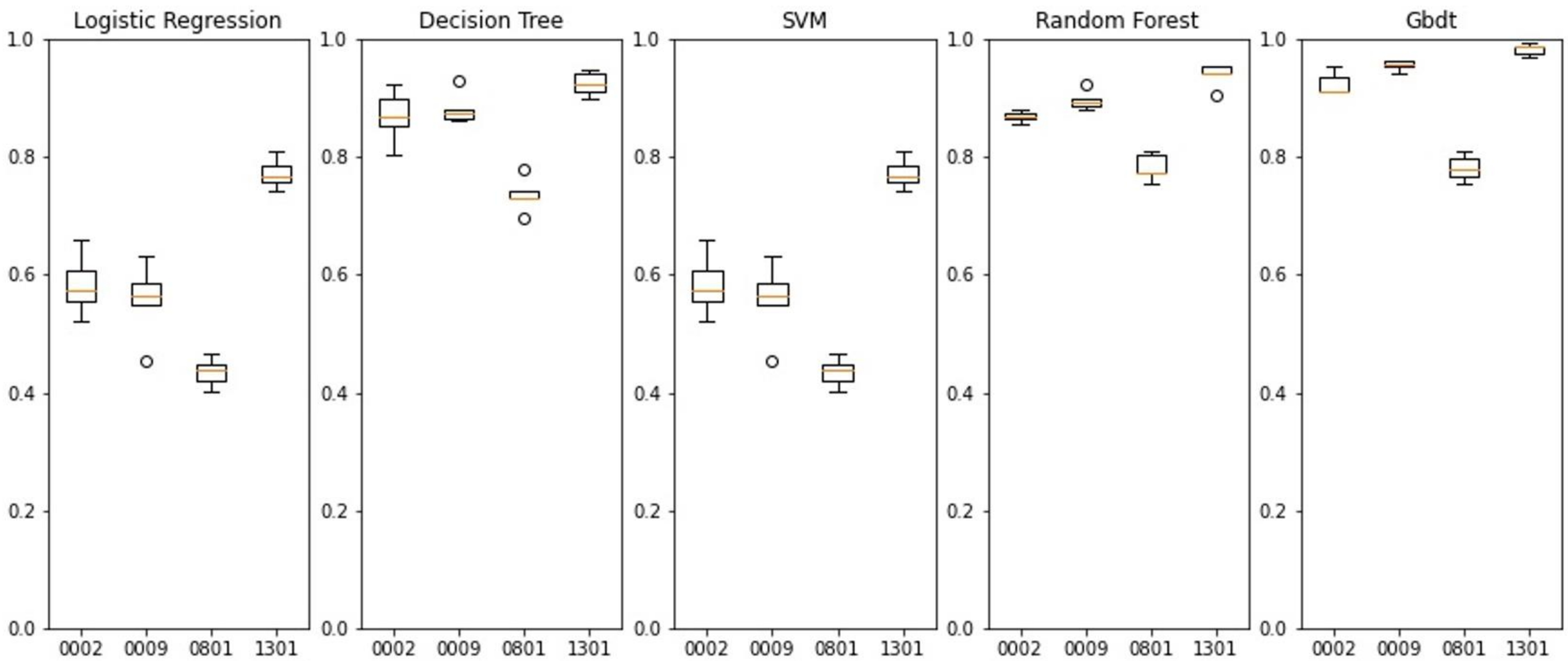
Preparing baseline dataset: visualizing separable features



Visualizing Fp1 & Fp2 power values of traditional frequency bands and sample entropy

Pre-experiment

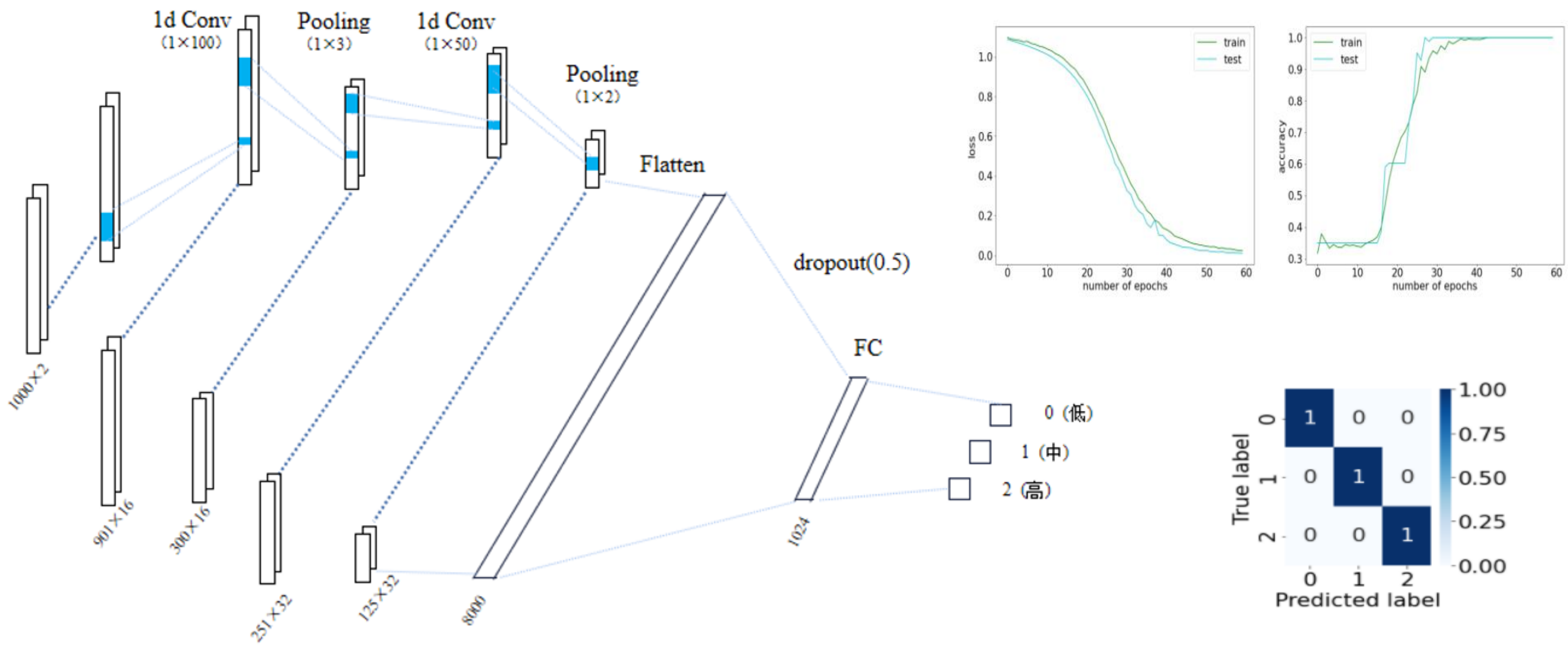
Comparing performances of different types of classic classifiers



Boxplot showing results of 5-fold validation on baseline dataset

Pre-experiment

Tuning CNN network



CNN structure + test result on baseline data (Single subject)

Comparative study

- **Pre-experiment: manual preprocessing**
  - **Not applicable in real-time processing due to time limitations (the frame rate)**
- **Experiment: automatic data preprocessing**

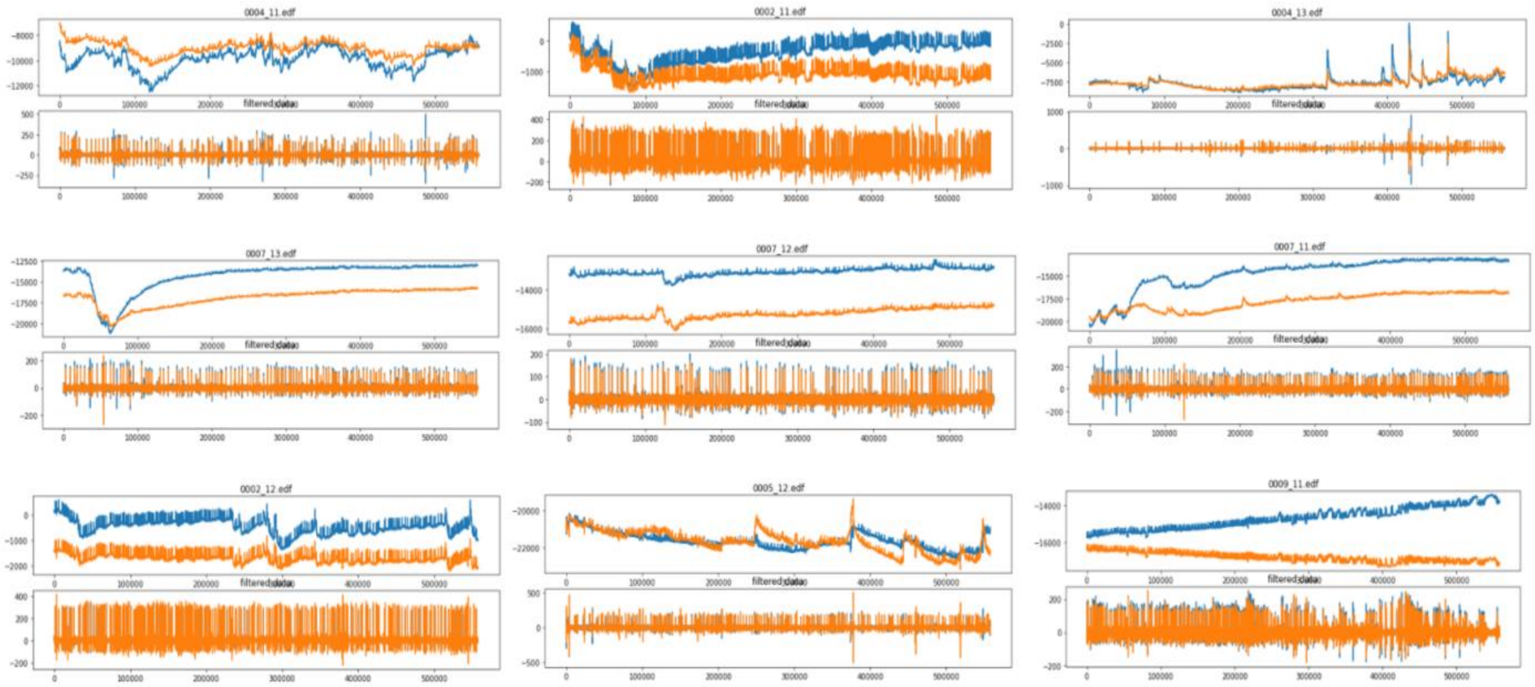
Comparative study

Automatic data preprocessing and quality control

- **Bandpass filtering: 1-30Hz**
- **Threshold rejection: ±60μV**
- **Normalization**

Comparative study

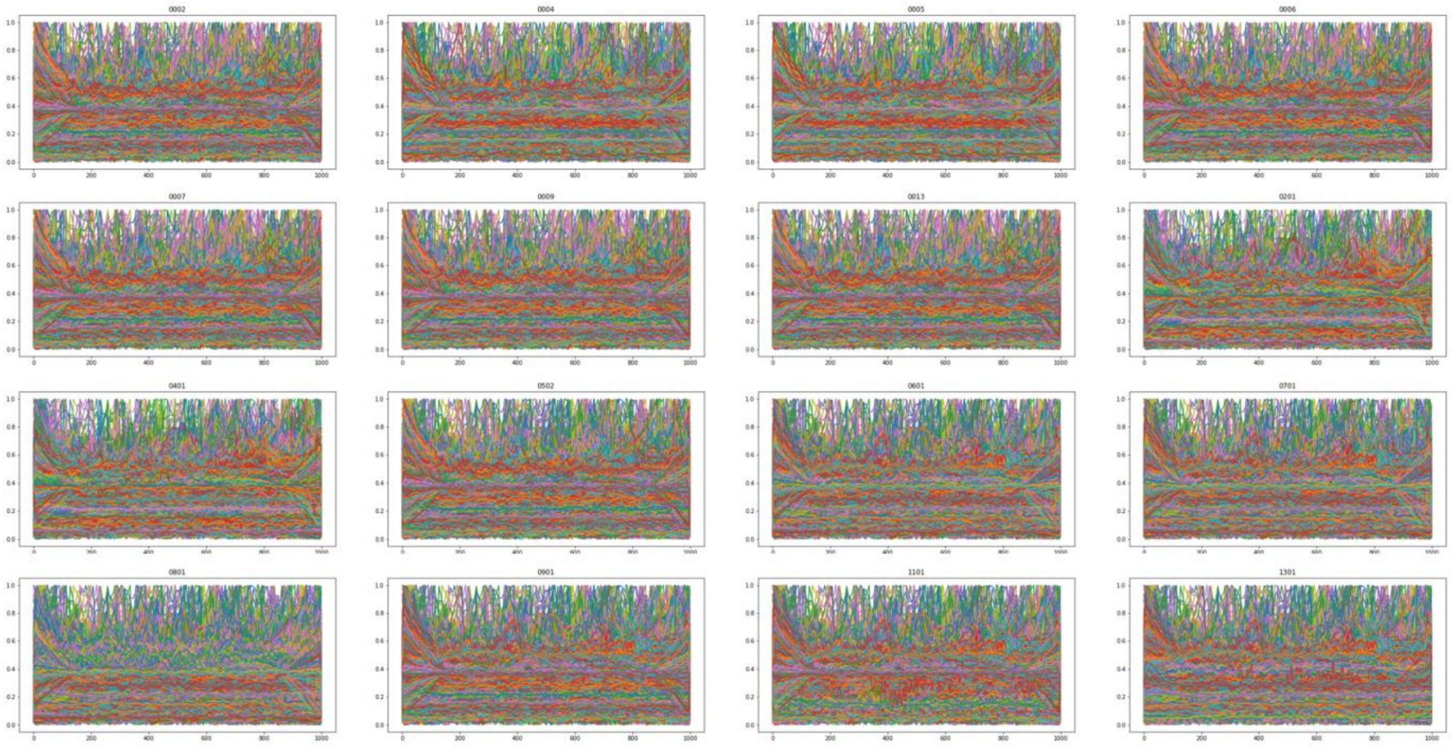
Automatic data preprocessing and quality control



Before and after 1~30Hz bandpass filtering

Comparative study

Automatic data preprocessing and quality control



Visualization to check data distribution (normalized to [0,1])

Comparative study

One data sample (2 channels, 1000 sample points) processed on Intel(R) Core i7-8550U CPU:

Start: 2021-01-08 01:49:08.425495

End: 2021-01-08 01:49:08.430481

Delta: 0.004986 s

Time consumed: less than 0.005s

Confirmed: available for real-time processing (0.5fps, input data: 2s short sequence)

Comparative study

subject	CNN	Logistic regression	Decision tree	SVM	Random forest	Gbdt
0002	1	0.5830411	0.8685344	0.5556031	0.8685771	0.9235386
0004	1	0.5538708	0.8444896	0.4569433	0.8301397	0.8971129
0005	1	0.4987881	0.9019461	0.4748788	0.9234602	0.9605147
0006	0.996	0.4552466	0.7395281	0.4838751	0.8147491	0.8446108
0007	1	0.466018	0.9163388	0.6893713	0.9247861	0.9642144
0009	1	0.5566724	0.8817508	0.6893499	0.8960721	0.9558169
0013	1	0.5604648	0.8458939	0.5879313	0.8972412	0.9283291
0201	0.96	0.415085	0.4854028	0.3859719	0.4721212	0.5534516
0401	0.927	0.4016556	0.4830007	0.3895196	0.4951515	0.554575
0502	0.996	0.4408397	0.6798332	0.5722341	0.6964927	0.7192686
0601	1	0.4335329	0.9041916	0.5832335	0.9365269	0.9748503
0701	1	0.4538922	0.8862275	0.4502994	0.8802395	0.948503
0801	0.984	0.4347305	0.7353293	0.4323353	0.7820359	0.7808383
0901	1	0.6893285	0.8673653	0.9617693	0.8877174	0.924722
1101	1	0.5268249	0.9486313	0.9163673	0.9605147	0.9856573
1301	1	0.7717779	0.9235672	0.8434702	0.9378529	0.9832549
AVG ±SD	**0.991 ±0.020**	**0.515 ±0.103**	**0.807 ±0.146**	**0.592 ±0.182**	**0.825 ±0.149**	**0.869 ±0.143**

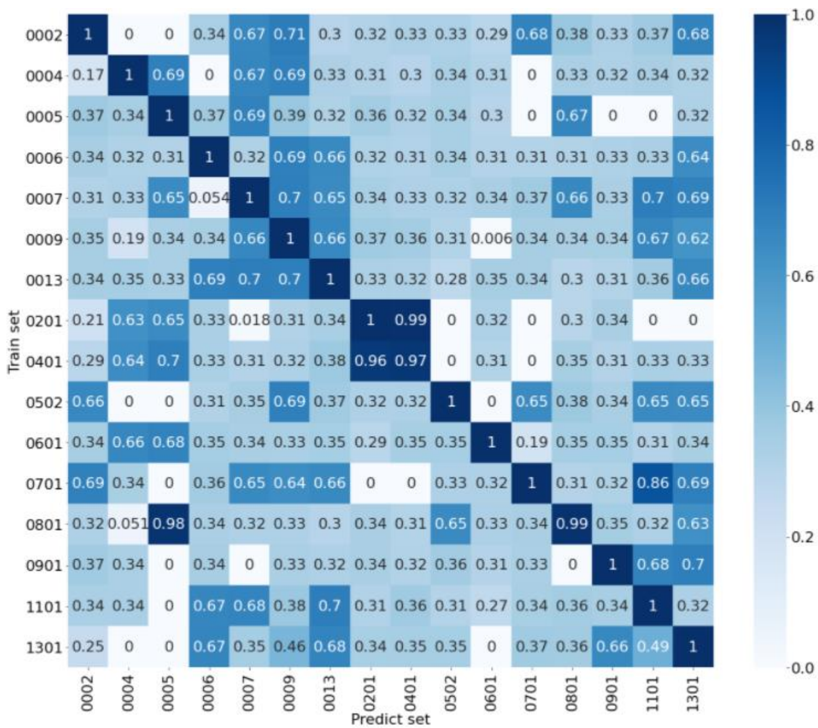
Effectiveness of the model: Single subject test

- **For each model: 1×16**
- **Classic classifiers: Gbdt 86%**
- **Deep learning: CNN 99%**
- **ANOVA (CNN vs Gbdt): p value = 4.9×10e-7**
- **SD (n=16) shows that CNN has the most stable performance in single subject test**

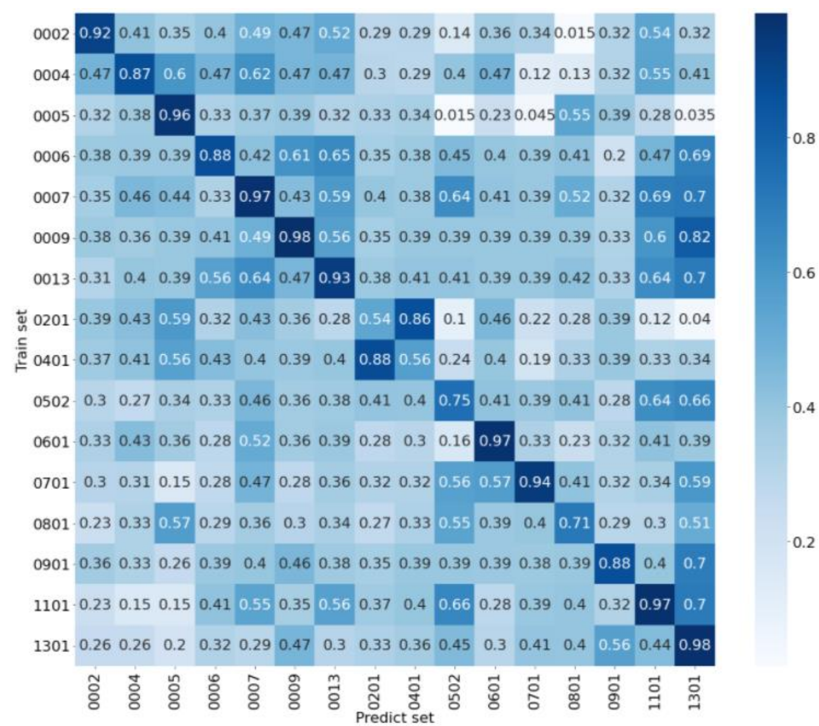
- **Compared with the classic classification model, CNN shows high accuracy and high stability in single subject test**

Comparative study

Versatility of the model: Single subject cross test



CNN



Gbdt

16 subjects, 256 tests performed.
Diagonal values: CNN near 1, Gbdt 0.75~1, confirming results in the single subject test.

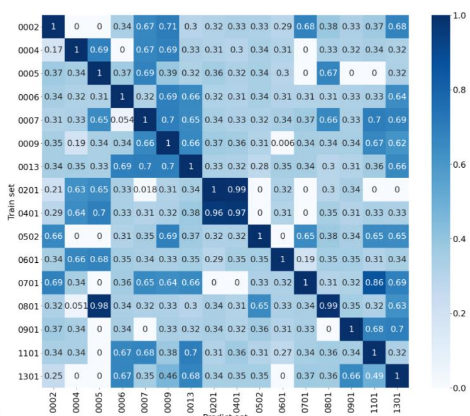
Comparative study

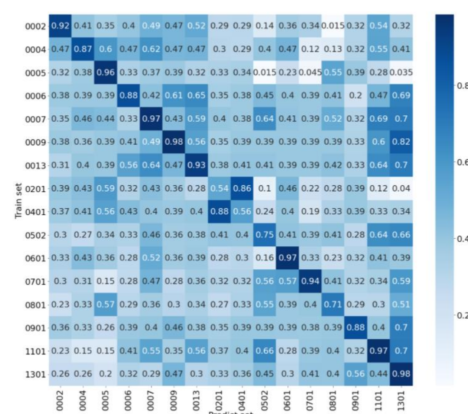
- **Control: random triple classification. Theoretical accuracy 33.33% assuming that data is evenly distributed.**
- **Reshape 16×16 matrices into 256×1 vectors, remove diagonal values. Average accuracy: CNN: 0.373, Gbdt: 0.389, both slightly higher than control**
- **ANOVA (CNN vs Gbdt): p value = 0.1543**
- **Randomness caused by individual differences affects the classification results considerably. Attention classification based on EEG should first consider using the data of the same individual for model training to ensure that the fitted model is applicable for the exact individual.**

Models trained on data of subject A should not be directly applied to the attentional level detection of subject B.

Comparative study

- **Apart from the diagonal values:**
  1. **More than half of the value is around 33%**
  2. **Approximately 1/4 of the values are around 67%**
  3. **Some values are very close to 0**
  4. **In merely 4 tests does the value reached above 80%**
- **Discussion: why do special values such as 0，33%，66% occur repeatedly**





Comparative study

subject	CNN	Logistic regression	Decision tree	SVM	Random forest	Gbdt
0002	0.333	0.412186	0.335723	0.379928	0.332139	0.336918
0004	0.359	0.307416	0.246411	0.349282	0.312201	0.312201
0005	0.305	0.251196	0.358852	0.348086	0.385167	0.368421
0006	0.468	0.363202	0.410992	0.400239	0.42055	0.359618
0007	0.427	0.421744	0.448029	0.44325	0.540024	0.630824
0009	0.538	0.289128	0.335723	0.483871	0.422939	0.464755
0013	0.594	0.414576	0.620072	0.462366	0.694146	0.615293
0201	0.472	0.387136	1	0.485437	1	0.580097
0401	0.802	0.387136	1	0.485437	1	0.580097
0502	0.329	0.439665	0.126643	0.396655	0.131422	0.317802
0601	0.323	0.51976	0.512575	0.335329	0.513772	0.500599
0701	0.333	0.372455	0.267066	0.353293	0.354491	0.346108
0801	0.598	0.410778	0.348503	0.449102	0.337725	0.495808
0901	0.667	0.345281	0.426523	0.34767	0.452808	0.339307
1101	0.609	0.517324	0.388292	0.37276	0.555556	0.593787
1301	0.99	0.401434	0.467145	0.473118	0.51374	0.574671
AVG ±SD	**0.51 ±0.20**	**0.39 ±0.07**	**0.46 ±0.24**	**0.41 ±0.06**	**0.50 ±0.23**	**0.46 ±0.12**

Versatility of the model: 16-fold cross test (15 for 1)

- **ANOVA (CNN vs Gbdt): p value = 0.2896**
- **Compared with the accuracy of single subject cross test (CNN: 0.373, Gbdt: 0.389), expanding and diversifying the training dataset gives better results (CNN: 0.51, Gbdt: 0.46). This improvement in the versatility of the models probably resulted from a decrease in randomness.**

Contents

Conclusion

- **Effectiveness of the model: single subject test (A->A)**
  - **Both the classic classification models and deep learning models are sufficient to use in classifying single-session data, CNN performs significantly better than ML models based on spectral/non-linear features.**
- **Versatility of the model: single subject cross test (A->B)**
  - **Low accuracy in all models constructed, indicating that individual differences exert significant effect on the versatility of models.**
- **Versatility of the model: multiple subjects cross test (others -> A)**
  - **Training on data of multiple subjects may reduce the randomness between individuals and improve versatility of the models.**

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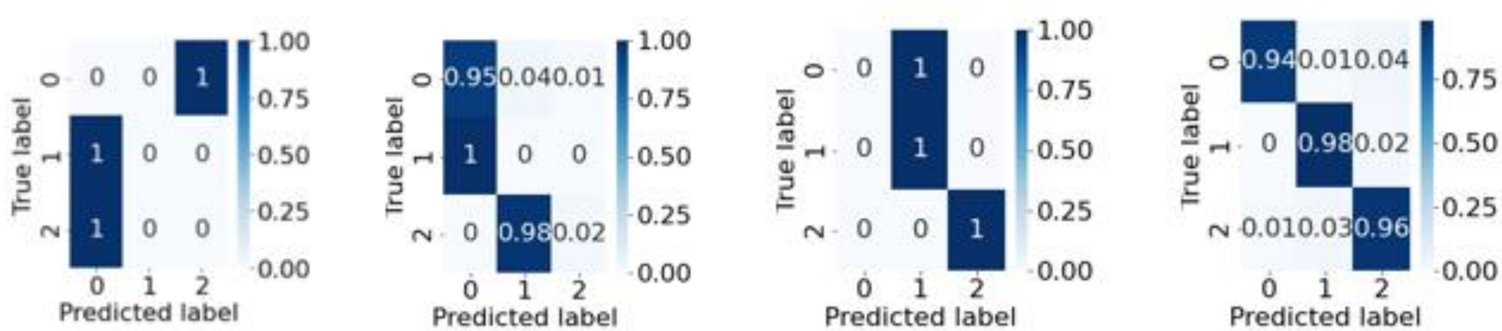
Error Analysis

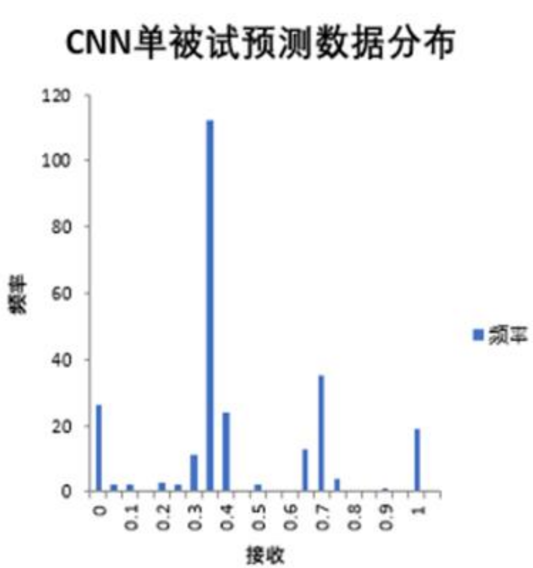
Possible sources of error

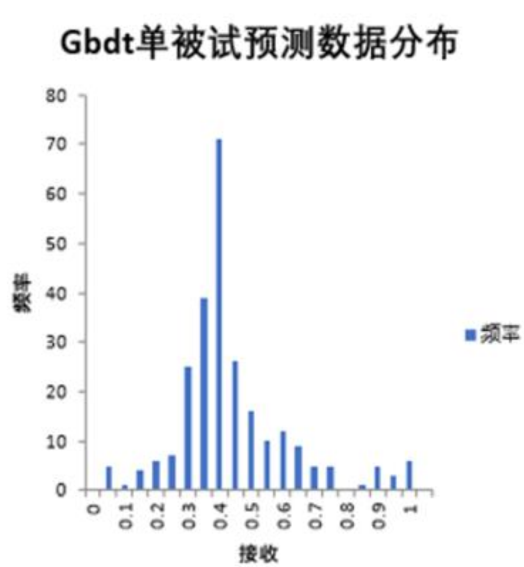
- **Noise in the dataset**
- **Randomness caused by individual differences**
- **Data distribution**



Confusion matrix for single subject cross test, left to right: near 0, 33% (1/3), 67% (2/3), 1

Error Analysis





CNN		Gbdt	
平均	0.373382458	平均	0.389375
标准误差	0.013554823	标准误差	0.008870098
中位数	0.337	中位数	0.385
众数	0	众数	0.39
标准差	0.209990421	标准差	0.13741496
方差	0.044095977	方差	0.018882871
峰度	0.160422204	峰度	1.648801325
偏度	0.279839402	偏度	0.461513204
区域	0.994	区域	0.865
最小值	0	最小值	0.015
最大值	0.994	最大值	0.88
求和	89.61179	求和	93.45
观测数	240	观测数	240

- **Visual inspection of data distribution: given the similar average values, the accuracies of CNN model fall more frequently in range [0.3,0.4] and [0.6,0.7], while for Gbdt model, the result is closer to a normal distribution.**

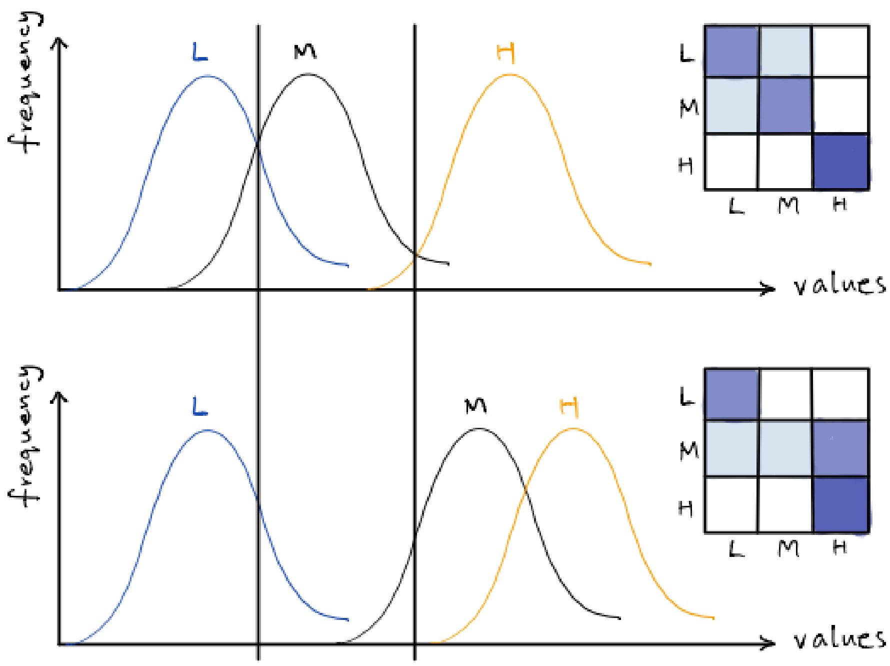
Error Analysis

Possible sources of error

- **Noise in the dataset**
- **Randomness caused by individual differences**
- **Data distribution**

(a)

(b)



Confusion in results of a tri-classification task: A -> B

Error Analysis

Discussion on real-time classification

- **We divide 3×10min EEG sequence into 2s short sequences so that the trained model would be usable under real-time restraints**
- **From A -> A test: Both CNN model and feature-based ML models are able to reach satisfying accuracy in single-session classification. Compared to existing studies, our model has higher classification accuracy and fair robustness, which should make it suitable for H/M/L attentional level monitoring in real world applications.**

Error Analysis

- **In real-world applications, consider:**
- **Using historical data from single subject as training set, and the fitted model to monitor attentional level of the same subject, or**
- **Using large-scale, varied EEG data set as training set, and the fitted model to monitor attentional level of new subjects**

Advantages and Disadvantages

Advantages

- **Design of the solution has exploited the characteristics of our dataset, the goal and background of the scientific problem**
  - **Real-time: short EEG sequences**
  - **Exploit the dataset: A -> A, A -> B, others -> A**
  - **Comparison of different models**
  - **Interdisciplinary: experimental design focuses on the combination of mental status and electrophysiological signals**

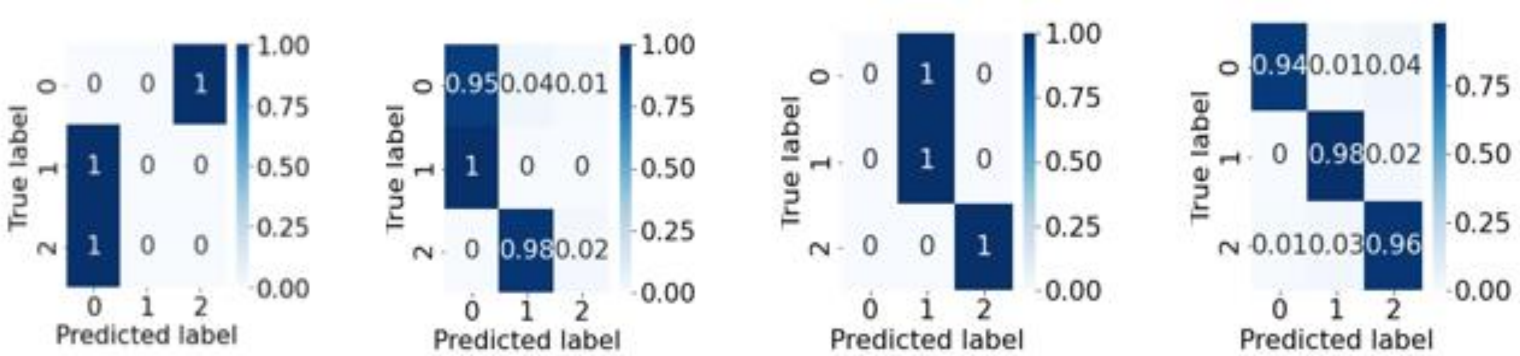
Disadvantages

- **Small dataset, Singular evaluation metrics, etc.**

Discussion

What about bi-classification?

- In tri-classification, we repeatedly see values near 0，33%，67%

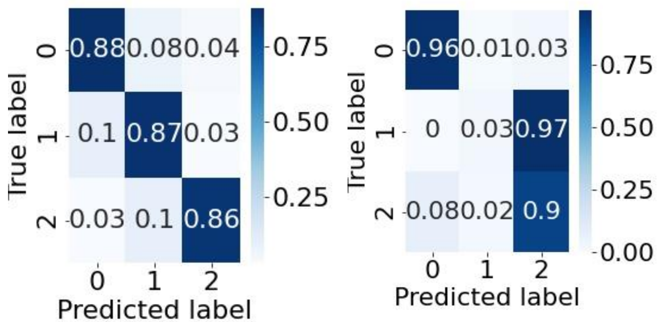


深入思考的问题

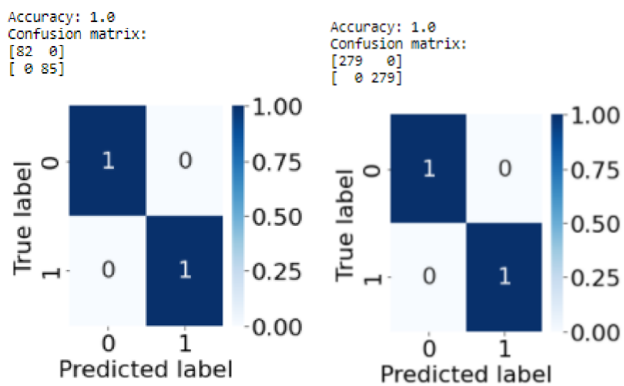
What about bi-classification?

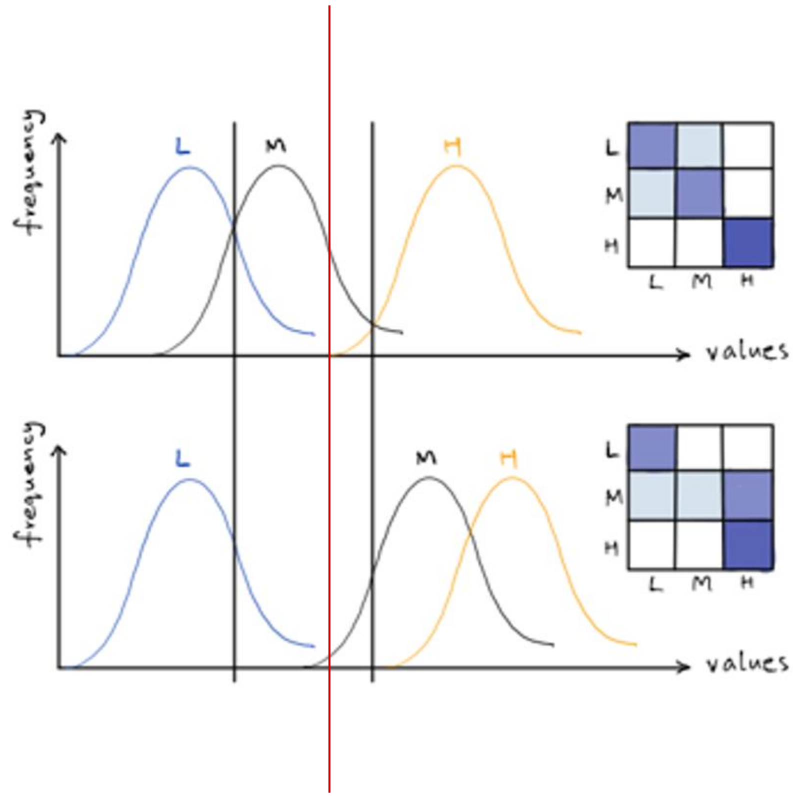
Sample: subject (0006, 0013)

(a)



(b)





Discussion

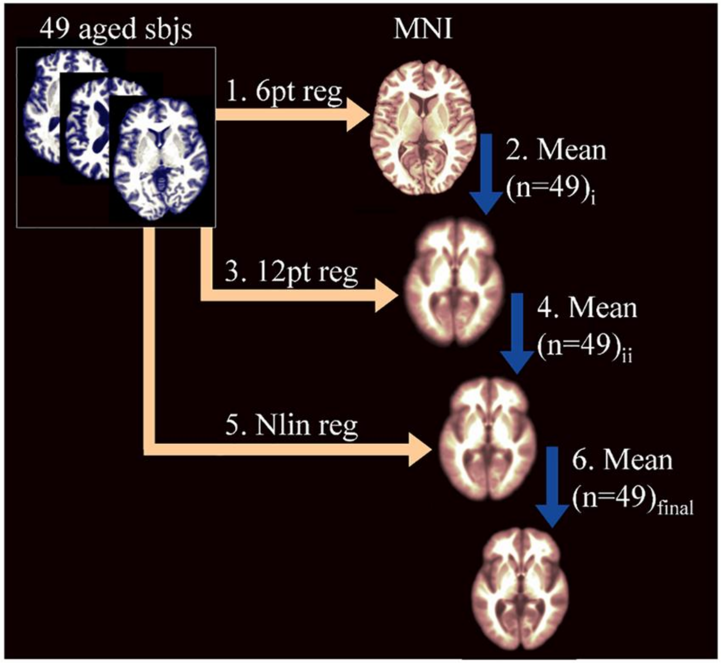
Fast pre-pocessing of EEG data

- **Koji et al. uses ±80μV as a threshold for EEG data cropping. Eoh et al. uses 50-70μV. Both reached satisfying results.**
- **Our study: filtration+60μV rejection threshold**
- **To apply more strict quality control on the consistency of our data, different rejection threshold should be adopted for different sessions, and standardizing transformation should be made on EEG sequences.**
- **Suitable solutions design for fast EEG pre-processing should consider:**
  - Metrics of EEG data distribution, such as expectation, variance, higher-order moments, convolutional features, nonlinear features, local features, etc.
  - Design of special mathematical transform that guarantees same distribution for all transformed data
  - Evaluation and validation of the transform method

Discussion

Standardizing EEG data: ideas inspired by MRI registration

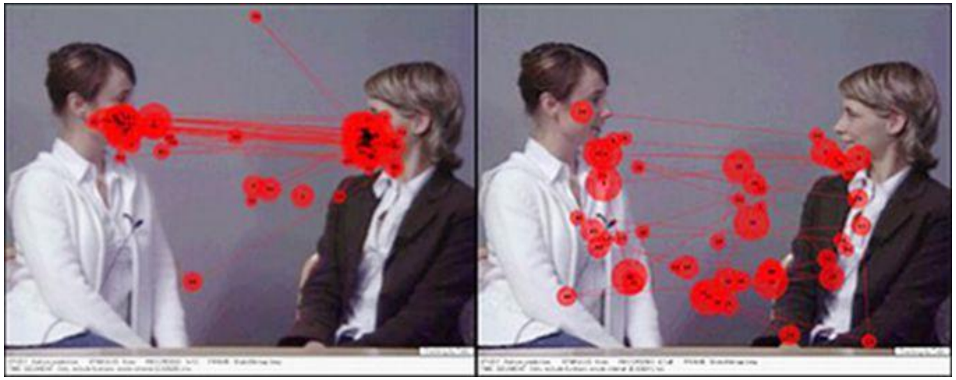
- The preprocessing of EEG can remove noise and artifacts in EEG data and greatly improve data quality. However, for data sets with a high degree of sample diversity, data standardization is also the key to data analysis, classification and data mining
- Taking MRI image processing as an example, the standardization of data processing and quality control procedures include orientation adjustment, registration and other necessary preprocessing, and then the brain image data of different subjects are mapped to a standard space, such as the MNI template (Montreal Neurological Institute Template))
- But for EEG data, there is still a lack of a unified preprocessing process



Discussion

Potential application in integrated attentional level detection

- **Some methods for attentional level detection may be used under limited conditions, thus can be applied as supplements to EEG detection.**
- **E.g. Monitor the driver's attentional level based on eye-movements**



- **Implementation of attentional level detection on mobile devices**
- **Improve the reliability using multi-channel detection methods**

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