EEG temporal–spatial transformer for person identification

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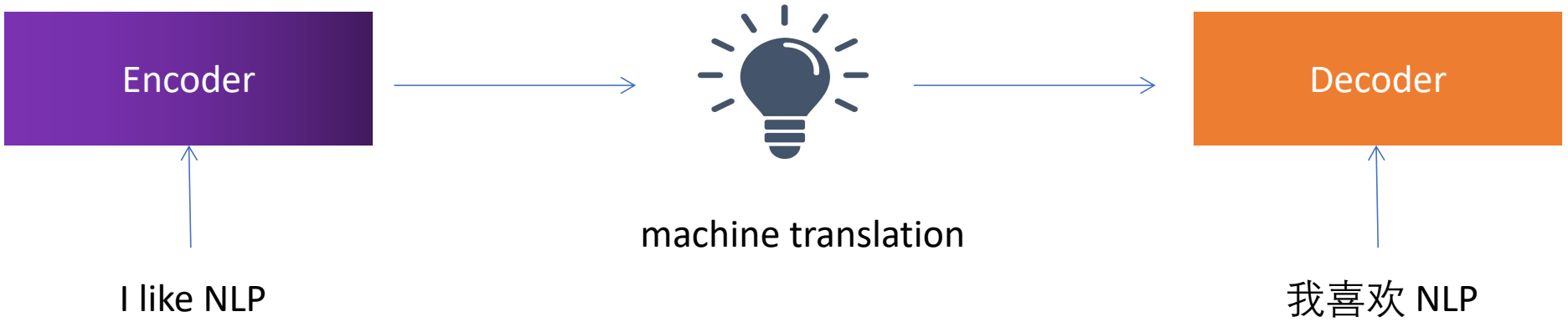
Research Problem

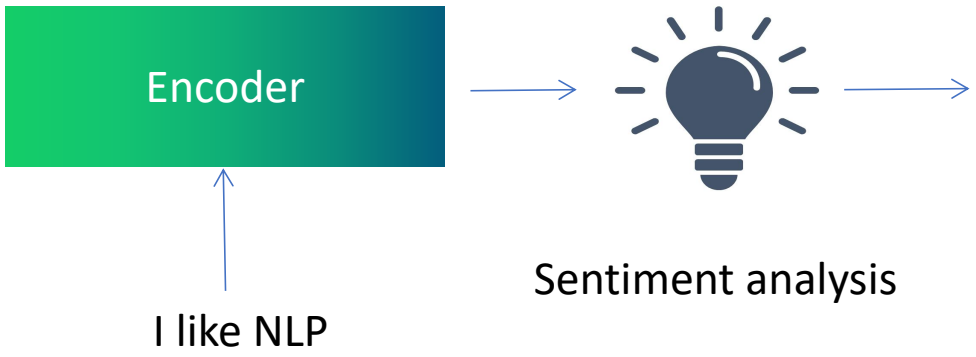
1. The importance of personal information security in a globalized world
2. Limitations of conventional biometric methods: fingerprint, face recognition.

Research Purpose

1. Need for more secure identification technologies

Transformer in NLP

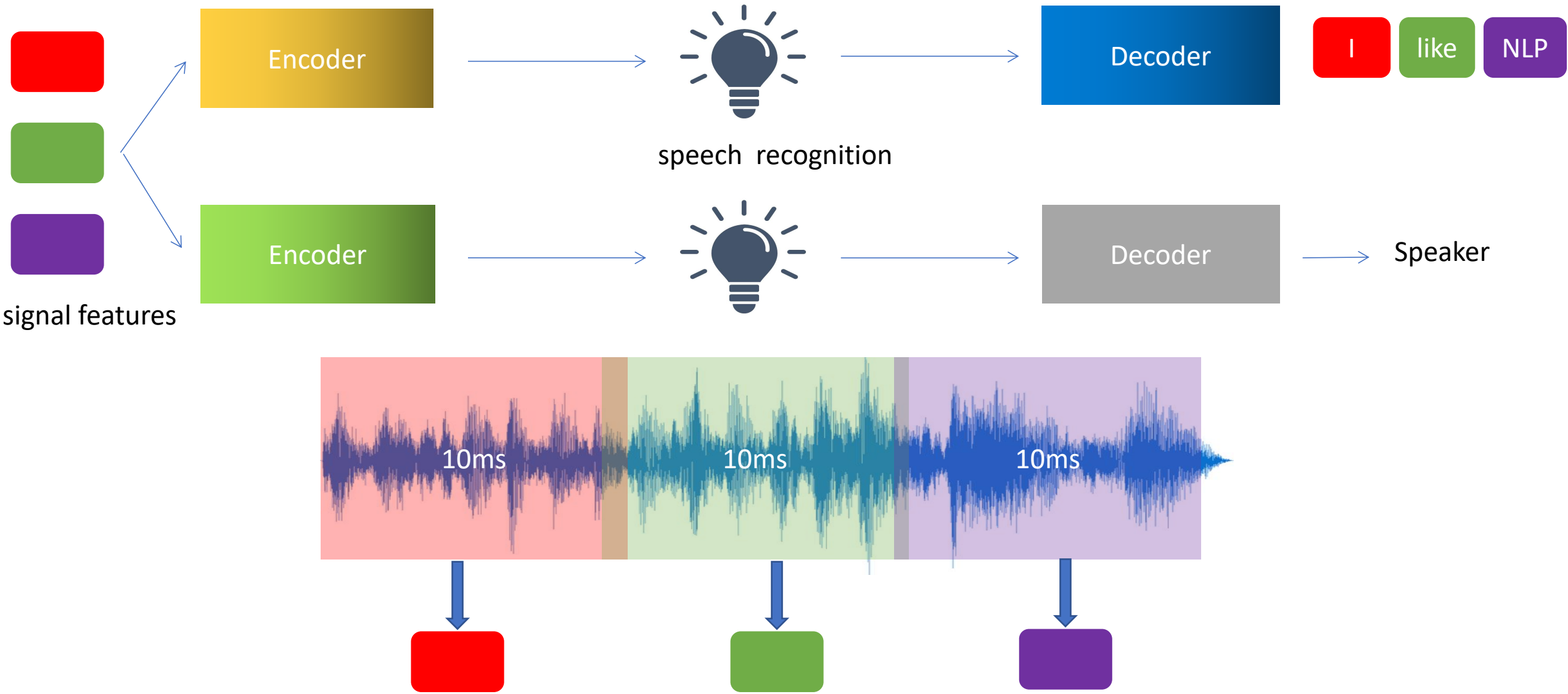




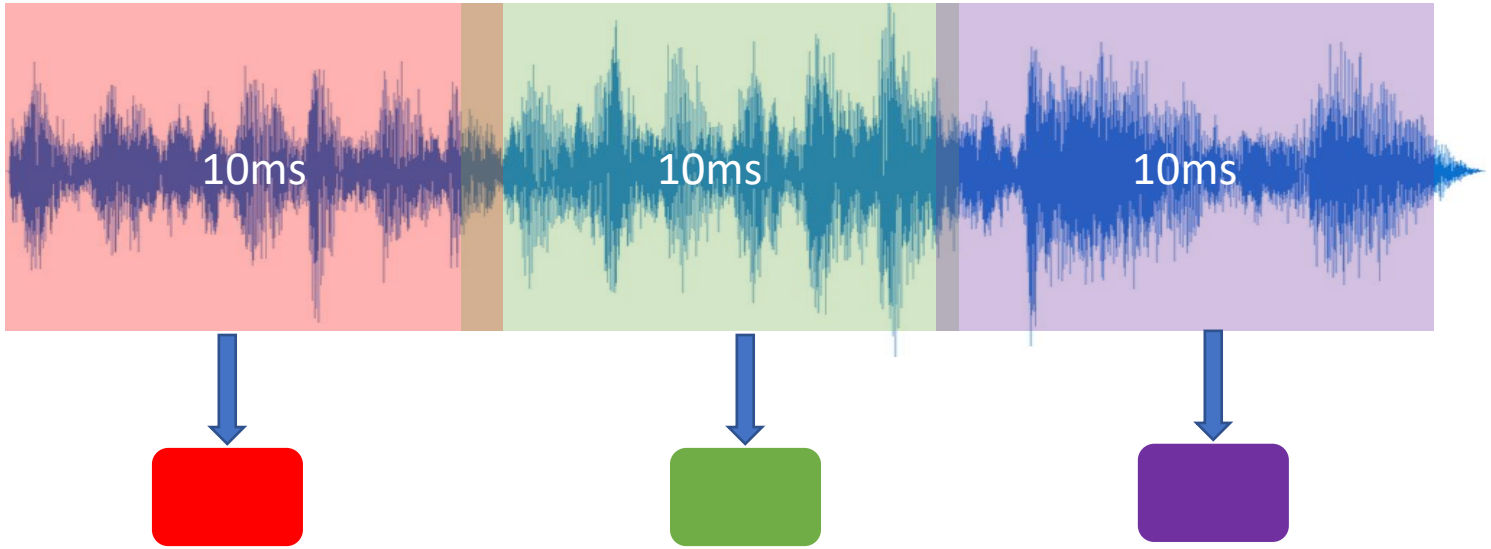
movie review

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive
5	Probably my all-time favorite movie, a story o...	positive
6	I sure would like to see a resurrection of a u...	positive
7	This show was an amazing, fresh & innovative i...	negative
8	Encouraged by the positive comments about this...	negative
9	If you like original gut wrenching laughter yo...	positive

Transformer in Signal



Signal Vectorization



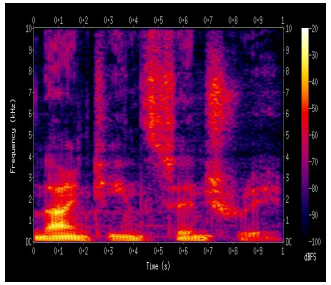
400 sample points

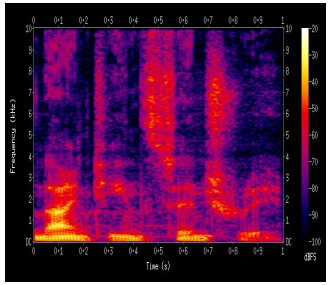
1 x 400

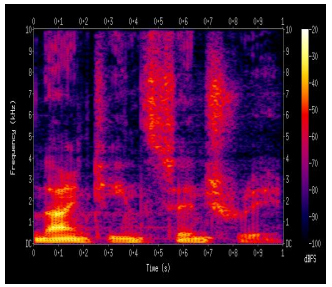
1 x 400

1 x 400

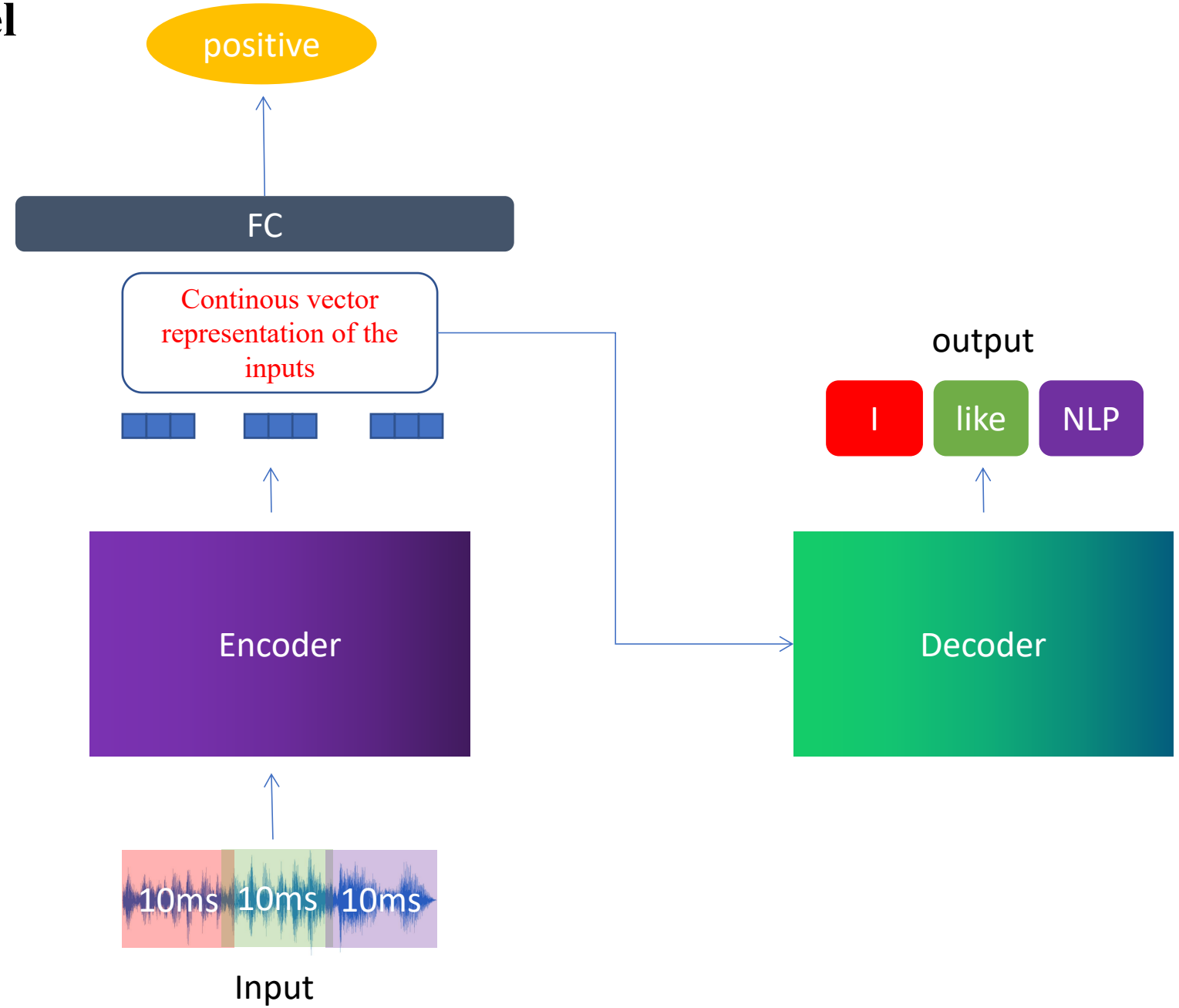
Spectrograms



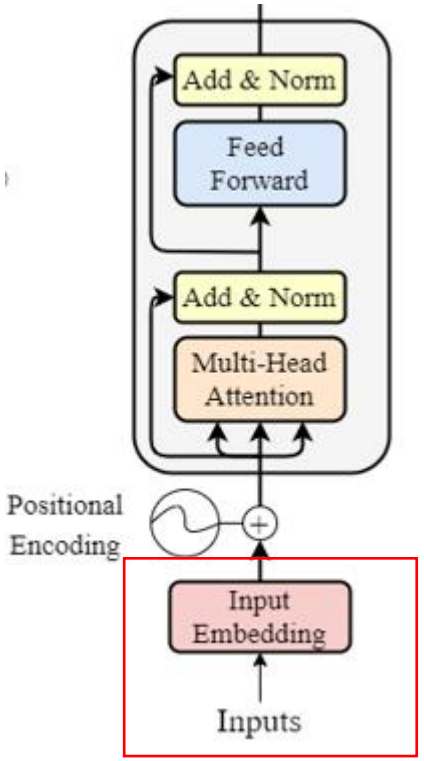


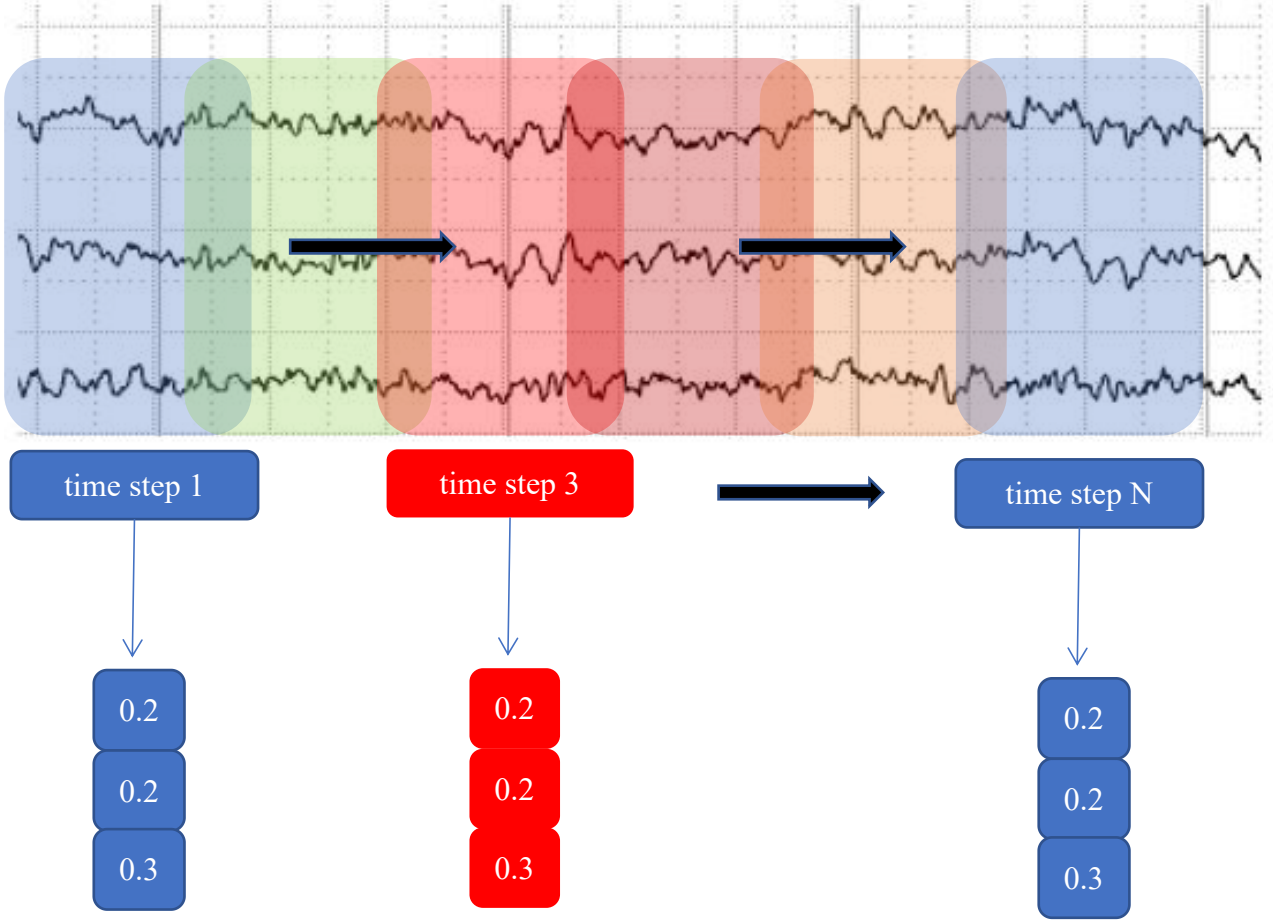


Transformer model



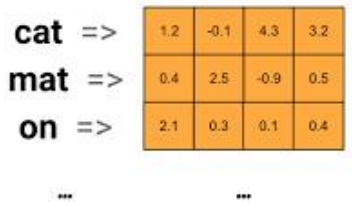
Encoder - input embedding



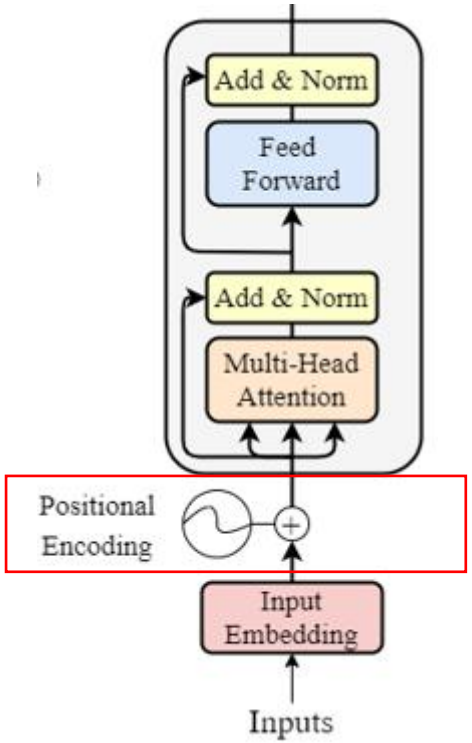


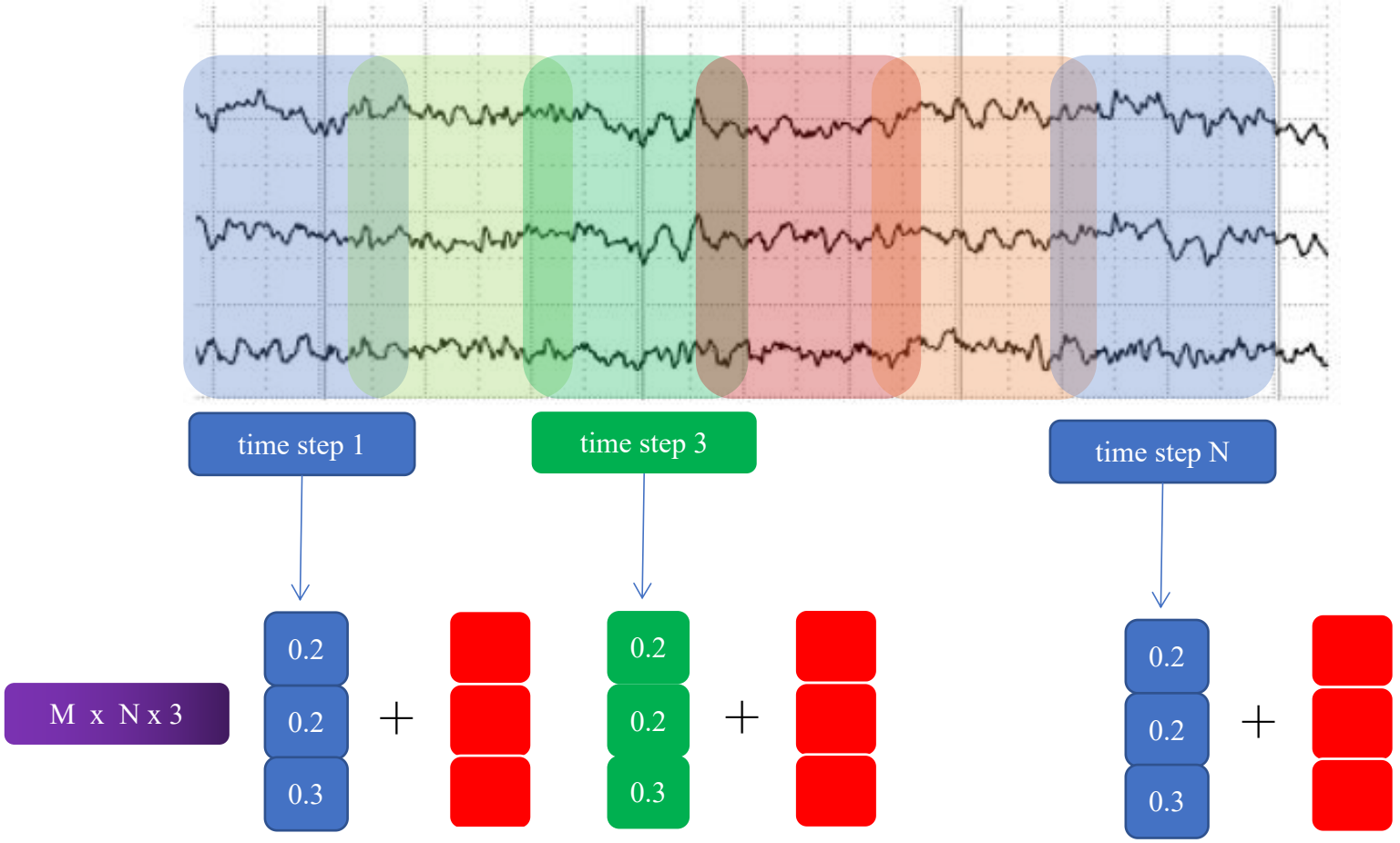
M x N x 3
(M is number of samples and N is number of timestep)

A 4-dimensional embedding



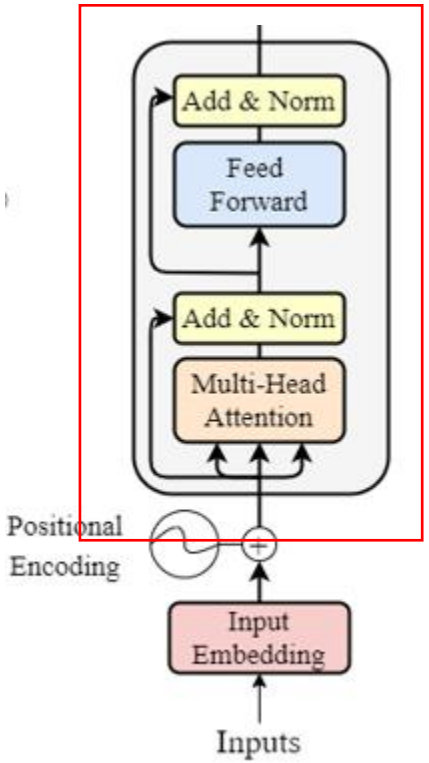
Encoder - position embedding





$$p_{i,j} = \begin{cases} \sin\left(\frac{i}{10000^{\frac{j}{d_{emb\_dim}}}}\right) & \text{if } j \text{ is even} \\ \cos\left(\frac{i}{10000^{\frac{j-1}{d_{emb\_dim}}}}\right) & \text{if } j \text{ is odd} \end{cases}$$

Encoder - position embedding



$$\text{softmax}\left(\frac{Q \times K^T}{\sqrt{d_k}}\right) V = Z$$

Encoder

Output Vectors

Z

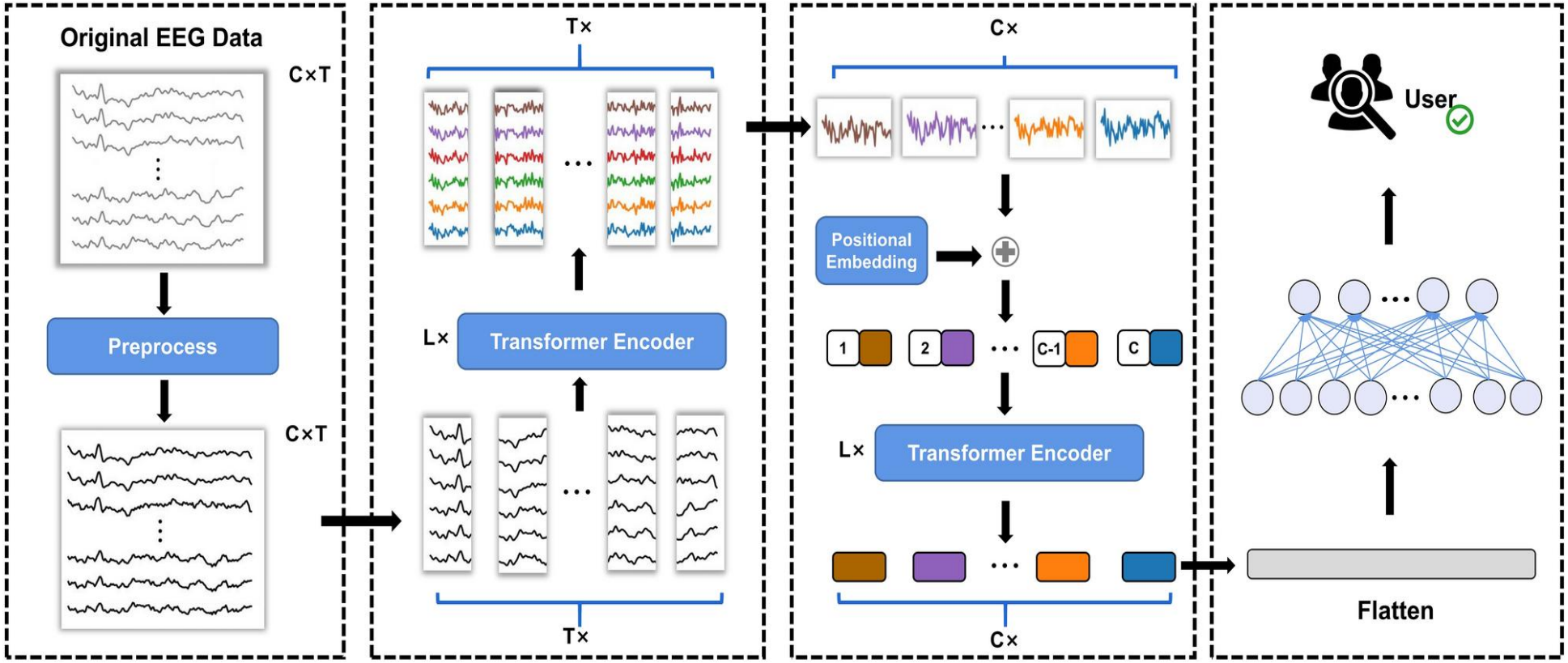
Z

Multi-head Attention

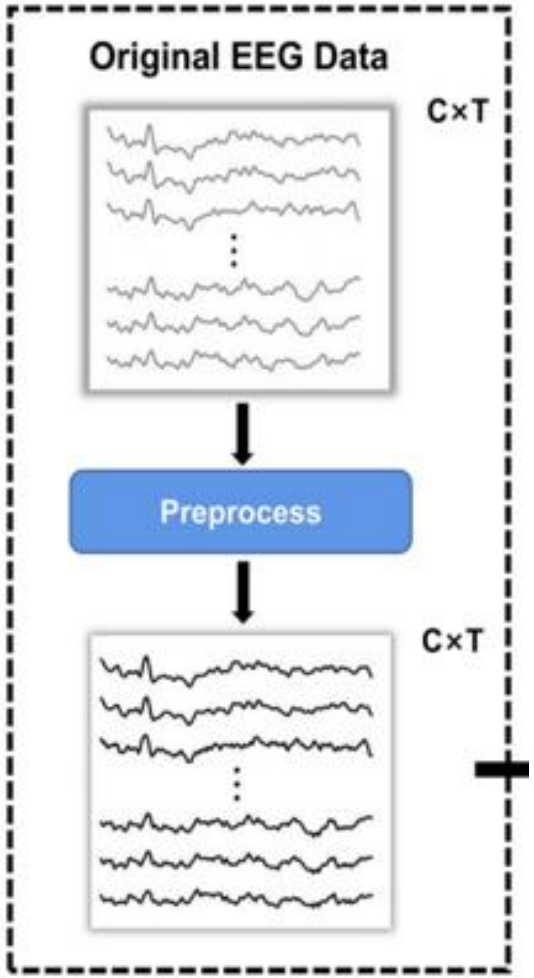
0.2
0.2
0.3

0.2
0.2
0.3

EEG temporal–spatial transformer for person identification



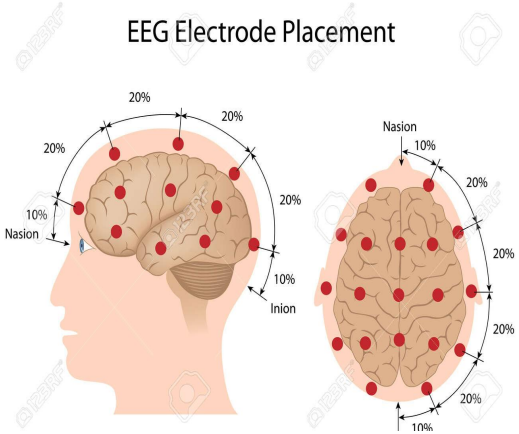
Preprocess



[0.5 42] Hz bandpass filter → Remove → low and high-frequency noises

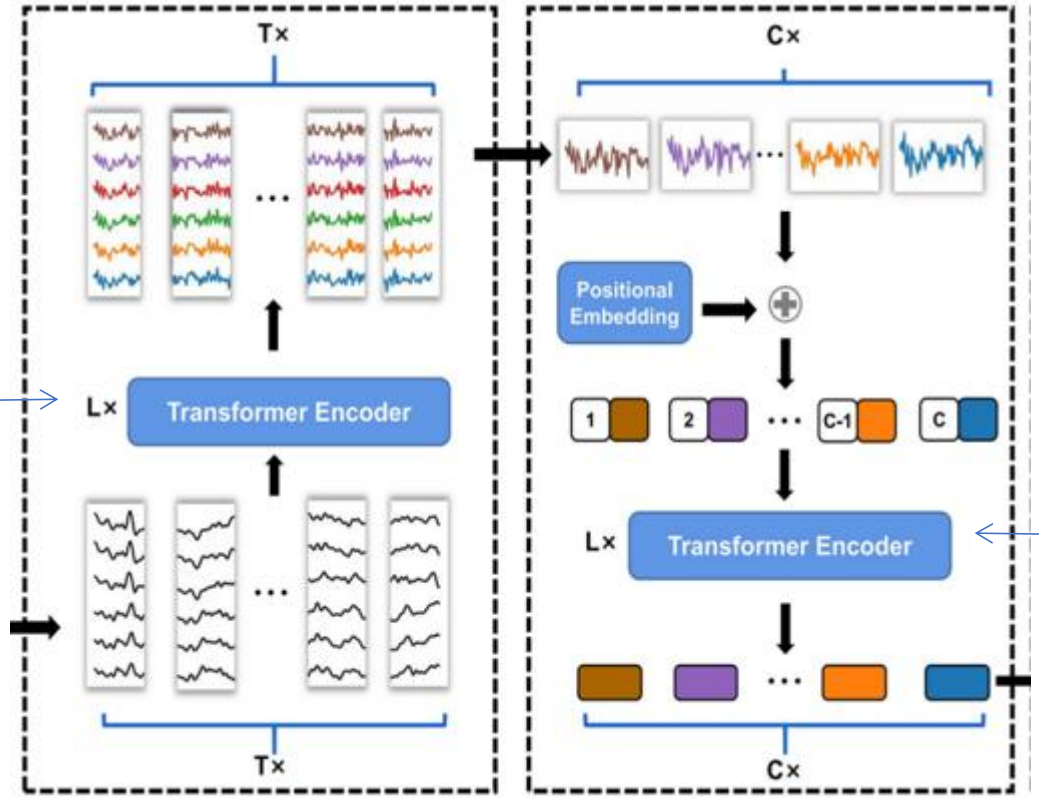
independent component analysis (ICA) → Remove → ocular and muscular artifacts

Transformer Encoder



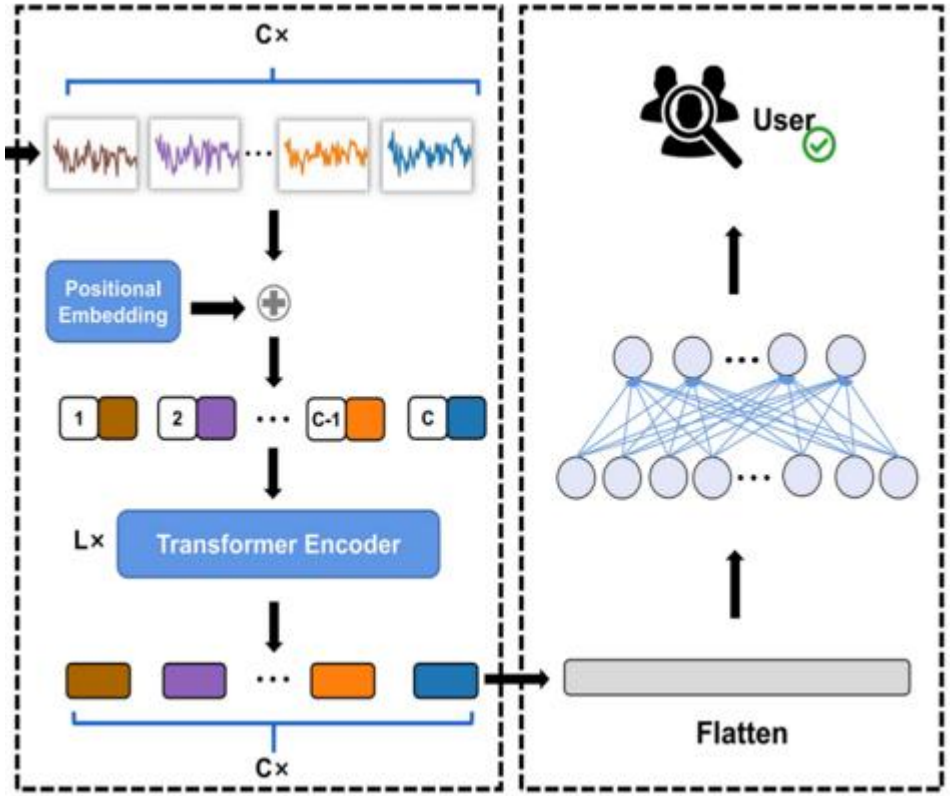
Temporal transformer:

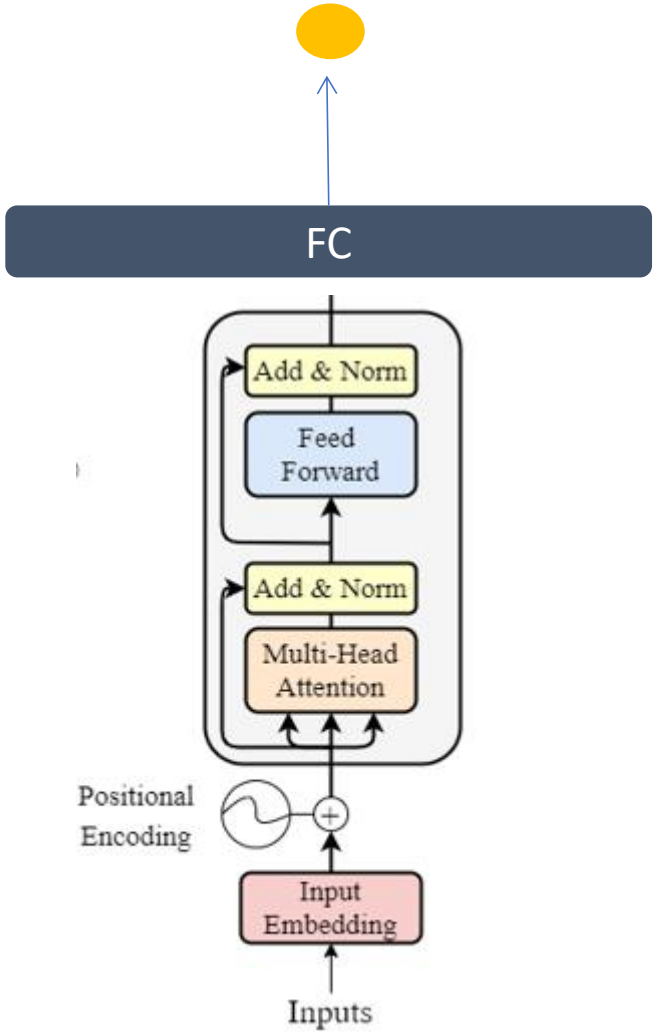
NO input embedding and positional enocidng



Spatial transformer

Transformer Encoder





Experiment design

1. Data:

- All subjects participate in both physical action (PHY) and imagined action (IMA) tasks, such as actual fist clenching and imagined fist clenching, while their EEG signals are recorded..

- Each subject's EEG is recorded using 64 electrodes with a sampling rate of 160 Hz.

2. Comparison experiments :

- Compared to traditional neural network methods such as CNN, MLP, and traditional machine learning methods such as SVM.

Table Results of models training on resting states and testing on diverse states

Method	PHY	IMA
FuzzEn + SVM[34]	16.16 ± 0.01	15.61 ± 0.00
Raw + CNN[34]	49.26 ± 3.85	52.51 ± 2.26
Graph + Mahalanobis distance[15]	69.98 ± 0.38	69.47 ± 0.64
PLV + GCNN[34]	85.40 ± 1.62	87.03 ± 2.53
Lite transformer[38]	87.37 ± 1.10	89.03 ± 0.73
EA-transformer[39]	89.47 ± 0.34	90.66 ± 0.39
Ours	**97.29 ± 0.03**	**97.45 ± 0.13**

Table Results of the ETST model with different position encoding.
PE (positional enocding)
physical action (PHY)
imagine completing the corresponding action (IMA)

Models	PHY	IMA
Non PE	95.84 ± 0.11	96.07 ± 0.03
With temporal PE	79.98 ± 13.03	80.89 ± 12.76
With spatial PE	**97.29 ± 0.03**	**97.45 ± 0.13**
With temporal + spatial PE	90.56 ± 1.94	91.20 ± 1.92