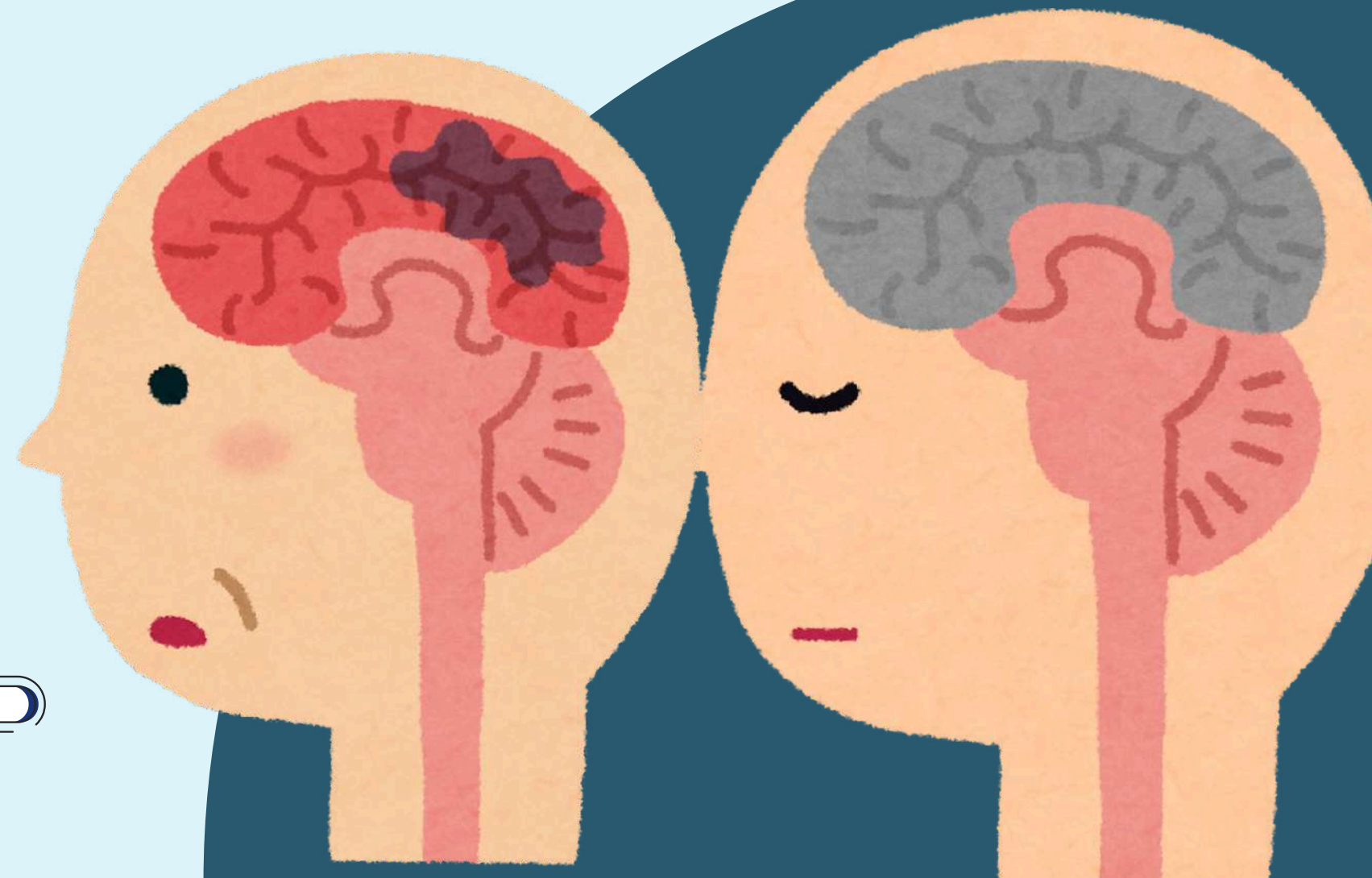
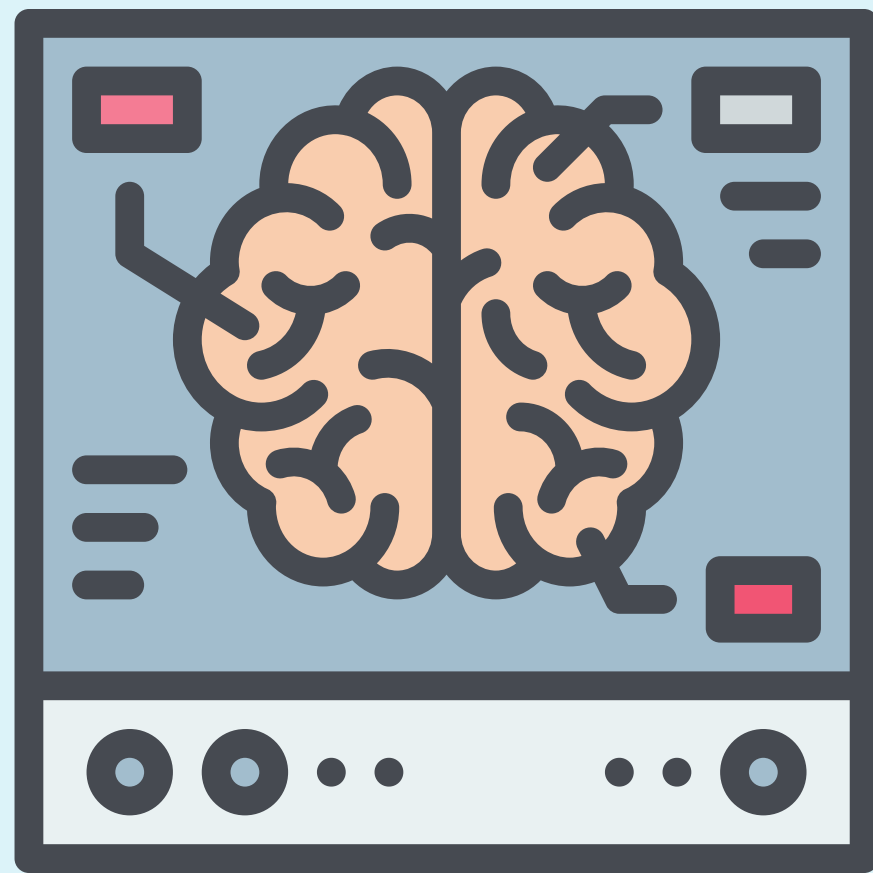
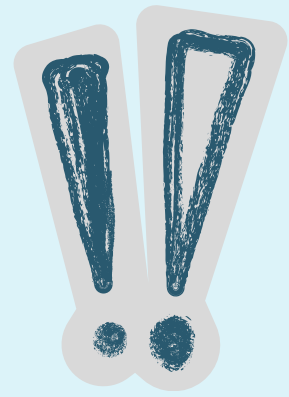


EEG-based Brain Stroke Detection and Localization

Team :- Om, Avni, Kashika





About 11.9 million
new stroke cases
occur globally every
year.

A piece of torn, light blue paper with a rough, irregular edge. The paper is centered on a white background. The text "PROBLEM STATEMENT" is printed in a bold, black, sans-serif font, centered on the paper.

**PROBLEM
STATEMENT**

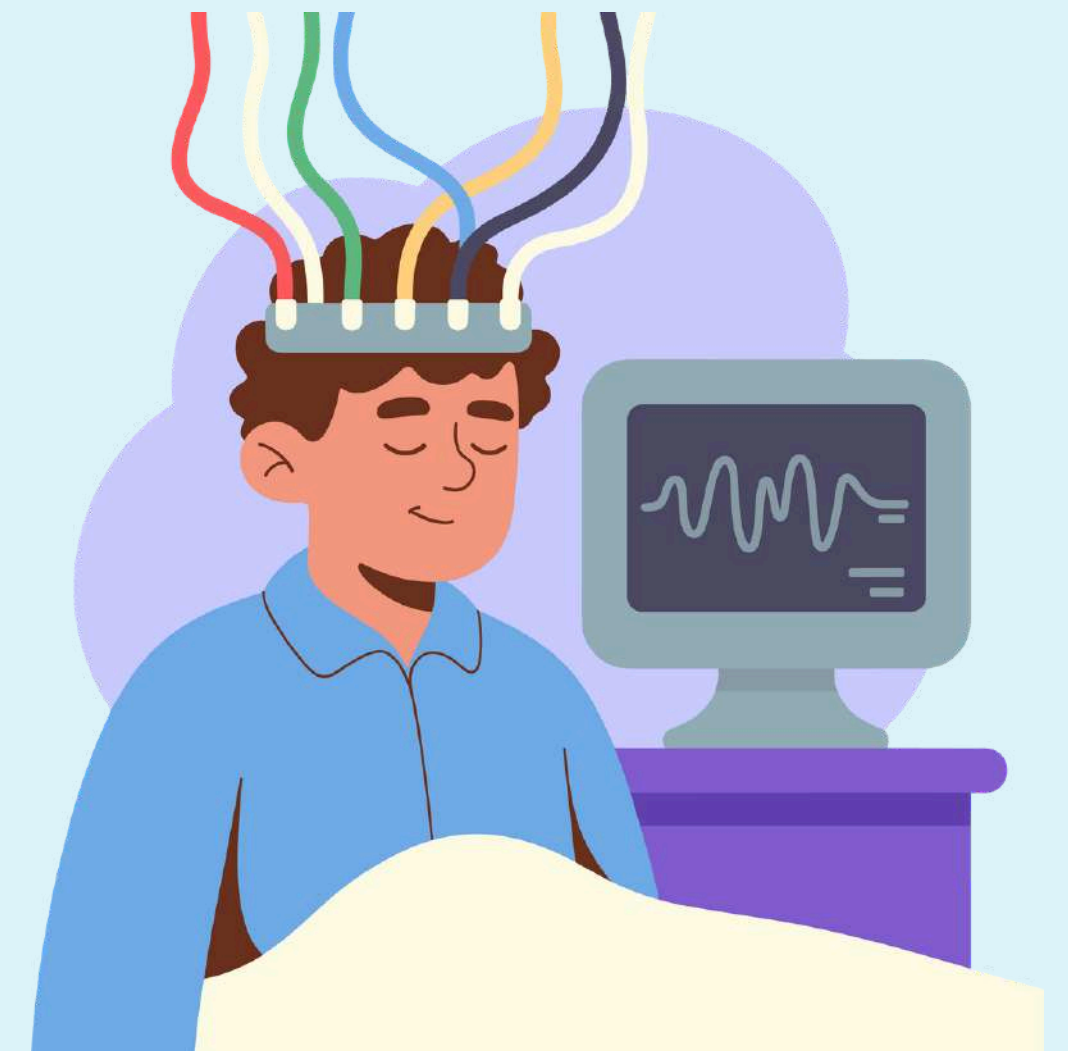
PROBLEM BEING SOLVED

Stroke diagnosis mainly relies on CT and MRI scans, which are costly, time-consuming, and not always readily available. While EEG provides a faster and non-invasive alternative, conventional EEG-based methods depend on manual feature extraction and channel-wise analysis, making it difficult to capture spatial relationships between brain regions and reliably detect stroke abnormalities.



POTENTIAL APPLICATIONS

- Rapid stroke screening in emergency departments using portable EEG-based AI analysis for faster preliminary diagnosis
- Continuous brain monitoring in intensive care units to detect abnormal neural activity and monitor stroke progression
- Early-stage stroke detection in remote or resource-limited healthcare settings where advanced imaging facilities are unavailable or delayed.



POTENTIAL IMPACT

- Reduces time required for stroke detection
- Improves accessibility to early diagnostic support
- Enables faster medical intervention and treatment
- Improves patient outcome
- Supports scalable screening using portable EEG devices





**LITERATURE
REVIEW**

Brain Symmetry Index in Healthy and Stroke Patients for Assessment and Prognosis

[Andrei Agius Anastasi](#)^{1,*}, [Owen Falzon](#)², [Kenneth Camilleri](#)², [Malcolm Vella](#)³, [Richard Muscat](#)¹

1. What other researchers did to solve the problem

Researchers investigated the use of quantitative EEG metrics, particularly the **Brain Symmetry Index (BSI)**, to measure differences in electrical activity between the two brain hemispheres in stroke patients. They recorded EEG signals during rest and motor tasks and compared stroke patients with healthy controls to detect abnormal hemispheric asymmetry.

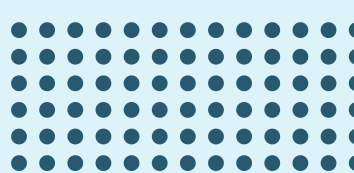

2. Developed solution from the study

The study introduced the Brain Symmetry Index as a biomarker for stroke analysis. Results showed that **BSI values were significantly higher in stroke patients**, indicating greater asymmetry in brain activity, and early BSI values correlated with later motor recovery outcomes measured using clinical scores such as the Fugl–Meyer scale.

3. How our project extends or improves this work

While this study relies on single EEG metrics and statistical analysis, our work extends it by using **machine learning** and deep learning models to automatically learn spatial patterns in EEG signals. By converting **EEG signals into topographic brain maps** and **applying CNN models**, we aim to capture more complex spatial abnormalities and improve stroke detection and localisation accuracy.

If you want, I can also help you with the next paper's slide, and I can make them consistent so all literature review slides follow the same structure, which usually impresses professors.



Surface electroencephalography (EEG) during the acute phase of stroke to assist with diagnosis and prediction of prognosis: a scoping review

Lou Sutcliffe ^{# 1}, Hannah Lumley ^{# 2}, Lisa Shaw ¹, Richard Francis ¹, Christopher I Price ¹

1. What other researchers did to solve the problem

Researchers conducted a scoping review of multiple clinical studies to evaluate how EEG has been used for early stroke identification and outcome prediction during the acute phase of stroke. The review examined whether EEG could distinguish stroke from stroke mimics, identify stroke subtypes, and help predict patient recovery during early clinical assessment.

2. Developed solution from the study

The review found that quantitative **EEG biomarkers** such as changes in delta, theta, alpha, and beta band activity, as well as indices like **delta-alpha ratios**, can help detect stroke-related brain abnormalities. Some studies also combined EEG features with clinical data or machine learning models, achieving promising diagnostic performance for detecting stroke and identifying large vessel occlusions

3. How our project extends or improves this work

Although EEG shows strong potential for stroke detection, the reviewed studies used different datasets, technologies, and EEG metrics, leading to inconsistent results and limited generalisation. Our project extends this work by **developing a standardised machine learning pipeline using EEG topographic maps and CNN models**, enabling automated detection of spatial brain activity patterns and improving consistency in stroke classification and localisation.

Deep Learning-Based Stroke Disease Prediction System Using Real-Time Bio Signals

[Yoon-A Choi](#)¹, [Se-Jin Park](#)², [Jong-Arm Jun](#)³, [Cheol-Sig Pyo](#)³, [Kang-Hee Cho](#)⁴, [Han-Sung Lee](#)^{5,*}, [Jae-Hak Yu](#)^{3,*}

1. What other researchers did to solve the problem

Researchers developed an **AI-based stroke prediction** system using real-time EEG signals. They explored the use of deep learning models to analyse brainwave data collected from **EEG sensors to detect stroke-related abnormalities** without relying on expensive imaging techniques.

2. Developed solution from the study

The study implemented and compared several deep learning models including LSTM, Bidirectional LSTM, CNN-LSTM, and CNN-Bidirectional LSTM for analysing EEG signals. The results showed that the **CNN-Bidirectional LSTM model achieved about 94% accuracy** in predicting stroke using raw EEG data, demonstrating the feasibility of automated stroke detection from brain signals.

3. How our project extends or improves this work

While this study focuses mainly on time-series deep learning models using raw EEG signals, our approach extends it by analysing **spatial patterns of brain activity using EEG topographic maps and CNN models**. This allows the model to capture hemispheric asymmetry and regional abnormalities more clearly, which can improve both stroke detection and localisation performance.

Convolutional Neural Network with a Topographic Representation Module for EEG-Based Brain–Computer Interfaces

[Xinbin Liang](#)¹, [Yaru Liu](#)¹, [Yang Yu](#)^{1,*}, [Kaixuan Liu](#)¹, [Yadong Liu](#)¹, [Zongtan Zhou](#)¹

1. What other researchers did to solve the problem

The researchers developed a CNN-based framework that preserves the spatial topology of EEG electrodes instead of treating EEG as only a 1D signal. They introduced a **Topographic Representation Module (TRM)** that maps EEG channels into spatial brain representations before CNN processing.

2. Developed solution from the study

The study created a CNN architecture capable of learning EEG spatial topological information using topographic representations of EEG signals. This **improved the CNN's ability** to capture relationships between electrodes and enhanced EEG classification performance.

3. How our project extends or improves this work

While this study focuses mainly on EEG classification for brain–computer interface applications, our project extends the idea toward medical stroke detection and localisation using EEG topographic brain maps. We further improve interpretability by **integrating Grad-CAM-based explainability** and abnormal activity visualisation. Our system also compares both classical ML methods (SVM) and deep learning approaches (CNN), making the framework **more clinically meaningful and deployable**.



Grad-TopoCAM: EEG Brain Region Visual Interpretability via Gradient-Based Topographic Class Activation Map

Liang Dong, Hengyi Shao, Lei Li, Lin Zhang

1. What other researchers did to solve the problem

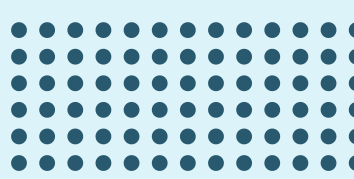
Researchers developed an explainable deep learning framework for EEG signal analysis to improve the interpretability of CNN-based EEG classification systems. They focused on identifying **which brain regions contributed most** to the model's predictions by applying Grad-CAM-based visualisation techniques to EEG spatial representations.

2. Developed solution from the study

The study introduced Grad-TopoCAM, a visualization framework that **combines CNN-based EEG decoding with Grad-CAM** interpretability methods. The system generated spatial attention **heatmaps** highlighting the EEG brain regions most influential in **classification decisions**, improving understanding of deep learning predictions on EEG data.

3. How our project extends or improves this work

While this study focuses mainly on explainable EEG decoding and brain-region visualization, our project extends the approach toward stroke detection and localisation using EEG topographic brain maps. We additionally integrate classical ML models such as **SVM for comparative analysis** and develop live topographic visualisation of abnormal neural activity over time, improving both interpretability and clinical applicability.



Research Paper	Limitations
1. Brain Symmetry Index in Healthy and Stroke Patients for Assessment and Prognosis	<ul style="list-style-type: none">• Relies on a single EEG metric (Brain Symmetry Index) to measure hemispheric asymmetry• Uses statistical correlation instead of an automated prediction model• Very small dataset (10 stroke patients and 10 healthy controls)• Cannot capture complex spatial patterns across multiple EEG electrodes
2. Surface Electroencephalography (EEG) during the Acute Phase of Stroke to Assist with Diagnosis and Prediction of Prognosis: A Scoping Review	<ul style="list-style-type: none">• Review study only, does not propose a new predictive model• Results across studies are inconsistent due to different datasets and technologies• Lack of standardised EEG biomarkers and analysis methods• Many approaches rely on manual feature extraction and clinical interpretation
3. Deep Learning-Based Stroke Disease Prediction System Using Real-Time Bio Signals	<ul style="list-style-type: none">• Focuses mainly on time-series EEG analysis• Does not explicitly model spatial relationships between electrodes• Limited ability to detect hemispheric asymmetry in brain activity• Does not use topographic EEG representations for spatial learning
4. Convolutional Neural Network with a Topographic Representation Module for EEG-Based Brain-Computer Interfaces	<ul style="list-style-type: none">• Focuses primarily on brain-computer interface (BCI) tasks rather than stroke detection• Requires large amounts of EEG data for effective CNN training• Does not incorporate temporal EEG dependencies across signal sequences• Lacks explainability and localisation methods for interpreting abnormal brain regions
5. Grad-TopoCAM: EEG Brain Region Visual Interpretability for Deep Learning Decoding. Dong et al.	<ul style="list-style-type: none">• Focuses mainly on EEG interpretability rather than direct stroke diagnosis or localisation.• Does not integrate clinical EEG biomarkers or frequency-band analysis for stroke detection.• Lacks comparison with classical ML models such as SVM for performance benchmarking.• Focuses only on explainability, while our system combines classification, localisation, and interpretability in a unified pipeline



**DATASET AND
FEATURES
PREPROCESSING**

DATASET OVERVIEW

1 Dataset: **EEG Motor Imagery Dataset for Brain-Computer Interface in Acute Stroke Patients**

Source: Scientific Data (Figshare)

- EEG recordings from 50 stroke patients
- Motor imagery tasks (left-hand / right-hand movement)
- EEG signals captured from multiple brain locations
- Suitable for studying stroke-related brain activity patterns

Dataset Size

- 50 subjects × 40 trials per subject
- Total trials = 2000 EEG trials

Data Structure

- Raw dataset format:
Trials × Channels × Time Samples
- Example:
2000 × 30 × 4000

```
      FP1      FP2      Fz      F3      F4      F7      F8 \
0  0.000110  0.000033  0.000026  0.000026  0.000034  0.000053  0.000044
1  0.000108  0.000032  0.000025  0.000025  0.000032  0.000052  0.000043
2  0.000107  0.000032  0.000024  0.000025  0.000031  0.000051  0.000043
3  0.000106  0.000031  0.000024  0.000025  0.000029  0.000050  0.000043
4  0.000106  0.000031  0.000023  0.000025  0.000028  0.000049  0.000043

      FCz      FC3      FC4      ...      P3      P4      T5      T6 \
0  0.000029  0.000057  0.000037  ...  0.000032  0.000016  0.000055  0.000014
1  0.000028  0.000057  0.000036  ...  0.000032  0.000018  0.000055  0.000016
2  0.000028  0.000056  0.000035  ...  0.000032  0.000020  0.000054  0.000019
3  0.000028  0.000056  0.000034  ...  0.000032  0.000021  0.000053  0.000022
4  0.000027  0.000055  0.000034  ...  0.000031  0.000023  0.000052  0.000024

      Oz      O1      O2      HEOL      HEOR
0  0.000077  0.000062  0.000050  0.000041  0.000051  0.000001
1  0.000081  0.000064  0.000055  0.000042  0.000050  0.000000
2  0.000084  0.000065  0.000061  0.000043  0.000049  0.000000
3  0.000087  0.000066  0.000066  0.000044  0.000048  0.000000
4  0.000089  0.000066  0.000070  0.000044  0.000046  0.000000

[5 rows x 33 columns]
```

WHY THIS DATASET?

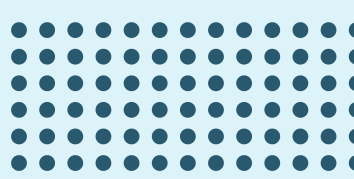
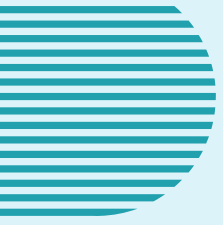
- Selected after identifying a research article that used this dataset for EEG-based stroke analysis
- The dataset contains EEG recordings from clinically diagnosed stroke patients, which directly aligns with our project objective of stroke detection
- Provides multichannel EEG signals recorded during motor imagery tasks, allowing analysis of stroke-related brain activity patterns
- Publicly available and well-documented dataset suitable for research and machine learning experiments

An EEG motor imagery dataset for brain computer interface in acute stroke patients

[Haijie Liu](#), [Penghu Wei](#), [Haochong Wang](#), [Xiaodong Lv](#), [Wei Duan](#), [Meijie Li](#), [Yan Zhao](#), [Qingmei Wang](#),
[Xinyuan Chen](#), [Gaige Shi](#), [Bo Han](#) & [Junwei Hao](#) 

[Scientific Data](#) **11**, Article number: 131 (2024) | [Cite this article](#)

27k Accesses | **49** Citations | **1** Altmetric | [Metrics](#)

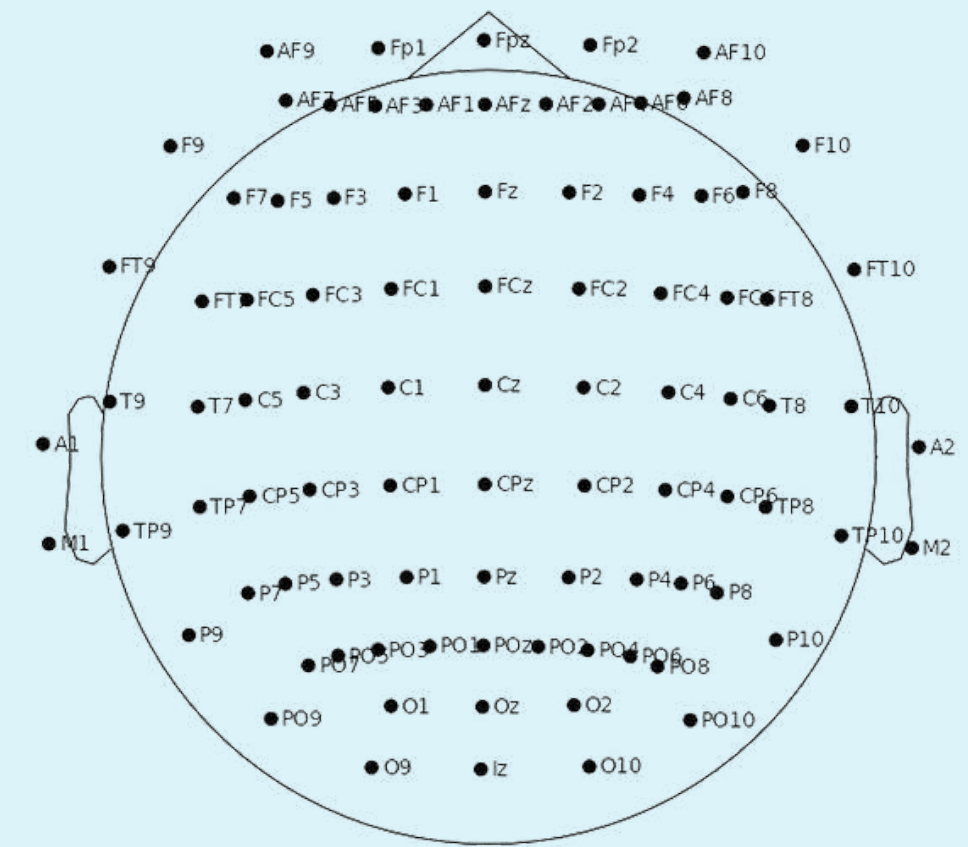


Data Collection of EEG Motor Imagery Dataset for Brain-Computer Interface in Acute Stroke Patients

- EEG recordings collected from 50 acute stroke patients at Xuanwu Hospital
- Data recorded 1–30 days after stroke onset
- Recorded using a wireless multichannel EEG system
- 30 EEG electrodes + 2 EOG electrodes placed using the international 10–10 electrode placement system.
- Sampling rate: 500 Hz
- Each patient performed 40 motor imagery trials

Experimental Procedure

- Patients imagined grasping an object with the left or right hand
- Each trial lasted 8 seconds and included:
 - Instruction phase
 - Motor imagery phase
 - Rest phase






DATASET OVERVIEW

2 Dataset: **EEG Motor Movement / Imagery Dataset**

Source: PhysioNet

- EEG recordings from 109 healthy subjects
- Motor execution and motor imagery tasks
- 64-channel EEG recordings for spatial brain analysis
- Used as non-stroke control data for comparison

Purpose

- Used as non-stroke control dataset
 - Enables comparison between normal and stroke-affected EEG activity
- 

WHY THIS DATASET?

- Selected as a healthy control dataset to represent normal brain activity
- Chosen after searching for a dataset with similar EEG characteristics (motor tasks and multichannel recordings) to ensure compatibility with the stroke dataset

	time	Fc5.	Fc3.	Fc1.	Fcz.	Fc2.	Fc4.	Fc6.	C5..	C3..	...	P8..	Po7.	Po3.	Poz.	Po4.	Po8.	O1..	Oz..	O2..	Iz..
0	0.00000	-5.0	2.0	37.0	39.0	30.0	26.0	-16.0	-14.0	4.0	...	-21.0	-8.0	-35.0	-45.0	-66.0	-39.0	-33.0	-48.0	-39.0	-39.0
1	0.00625	-12.0	-24.0	1.0	-2.0	-15.0	-22.0	-55.0	-36.0	-27.0	...	-50.0	-40.0	-68.0	-65.0	-84.0	-52.0	-21.0	-42.0	-31.0	-34.0
2	0.01250	-77.0	-78.0	-59.0	-65.0	-63.0	-55.0	-67.0	-88.0	-71.0	...	-17.0	-22.0	-50.0	-35.0	-48.0	-18.0	-20.0	-42.0	-29.0	-27.0
3	0.01875	-66.0	-67.0	-50.0	-65.0	-60.0	-55.0	-68.0	-62.0	-53.0	...	-39.0	-60.0	-78.0	-64.0	-68.0	-41.0	-44.0	-62.0	-34.0	-43.0
4	0.02500	-45.0	-55.0	-33.0	-53.0	-54.0	-63.0	-83.0	-52.0	-50.0	...	-44.0	-55.0	-70.0	-54.0	-63.0	-37.0	-60.0	-70.0	-34.0	-45.0

5 rows × 65 columns



Data Collection of EEG Motor Movement / Imagery Dataset (PhysioNet)

Non-Stroke Patients

- EEG recordings collected from 109 healthy subjects
- Data recorded using the BCI2000 EEG acquisition system
- 64 EEG electrodes placed according to the international 10–10 system
- Sampling rate: 160 Hz
- Each subject performed multiple motor execution and motor imagery tasks

Experimental Procedure

Participants performed motor movement and motor imagery tasks.

Tasks included:

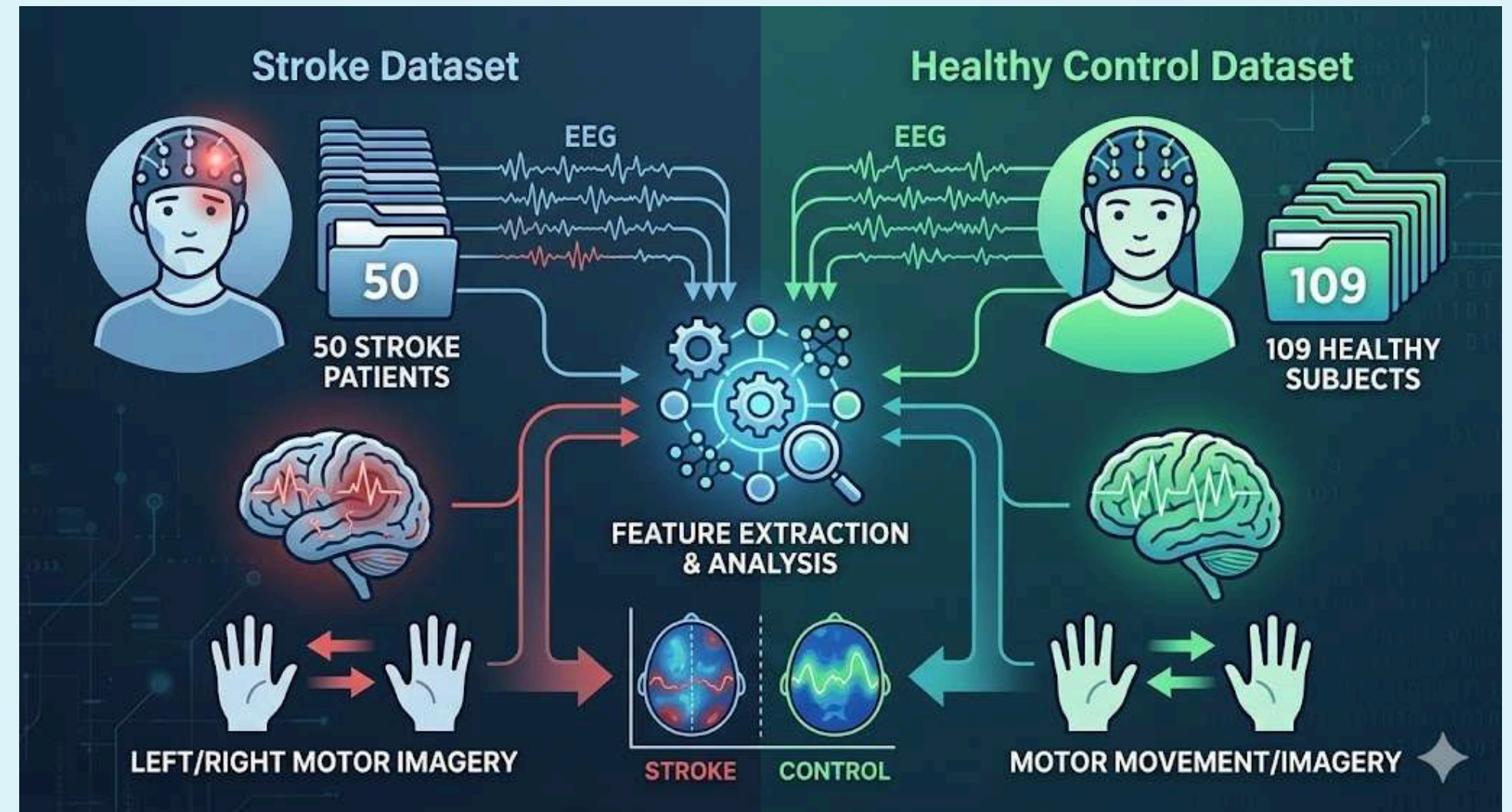
- Left-hand movement or imagery
- Right-hand movement or imagery
- Both hands movement or imagery
- Both feet movement or imagery

Each trial included:

- Instruction cue
- Motor execution / motor imagery phase
- Rest period

Ethical Considerations

- Study approved by the Ethics Committee of Xuanwu Hospital
- Participants provided informed consent
- Data was anonymised before public release





DATASET PREPROCESSING

EEG Data Description

- EEG recordings were collected from stroke and non-stroke subjects.
- The recordings were processed in EDF format.
- Since both datasets had different channel structures, a common set of EEG channels was selected.
- Non-EEG/EOG-related channels were excluded to reduce artifacts and maintain consistency.

Step 1: Channel Selection

- 26 Common EEG channels were selected across stroke and non-stroke recordings.
- Channel names were standardized before processing.
- Only brain-signal-related channels were retained.

Purpose:

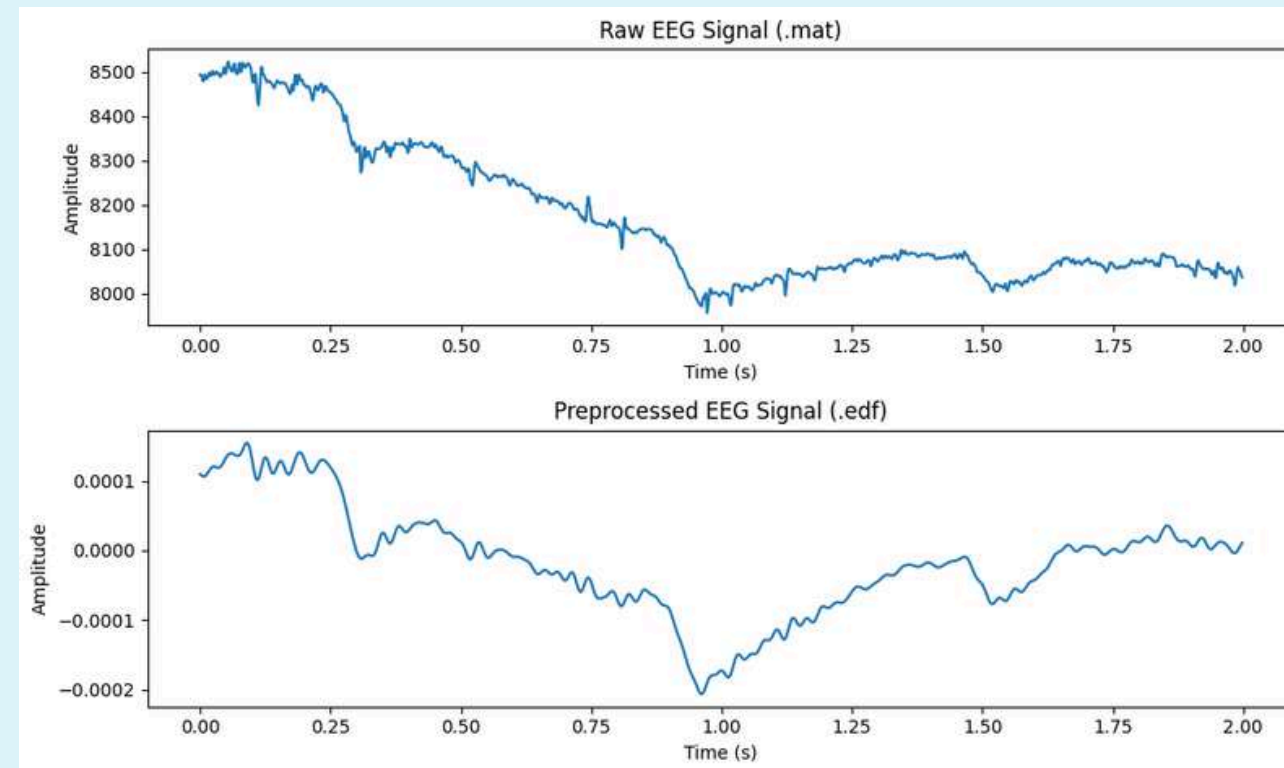
To ensure that both classes use the same EEG channel structure before model training.

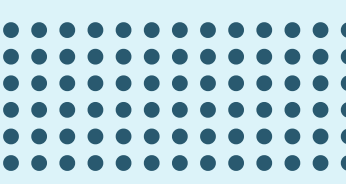
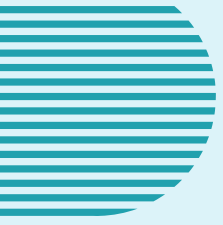
Step 2: Signal Preprocessing

- EEG signals were resampled to a common sampling frequency.
- A Butterworth band-pass filter of 0.5–40 Hz was applied.
- Low-frequency drift (<0.5) and high-frequency noise (>40) were reduced.

Purpose:

To retain physiologically meaningful EEG frequency components.





Model-Specific Data Preparation

SVM Pipeline:

- Preprocessed EEG signals were converted into numerical feature vectors.
- Power Spectral Density was computed using Welch's method.
- Band power features were extracted from EEG frequency bands:
 - Delta: 0.5–4 Hz
 - Theta: 4–8 Hz
 - Alpha: 8–13 Hz
 - Beta: 13–30 Hz
- These handcrafted features were used to train the SVM classifier.

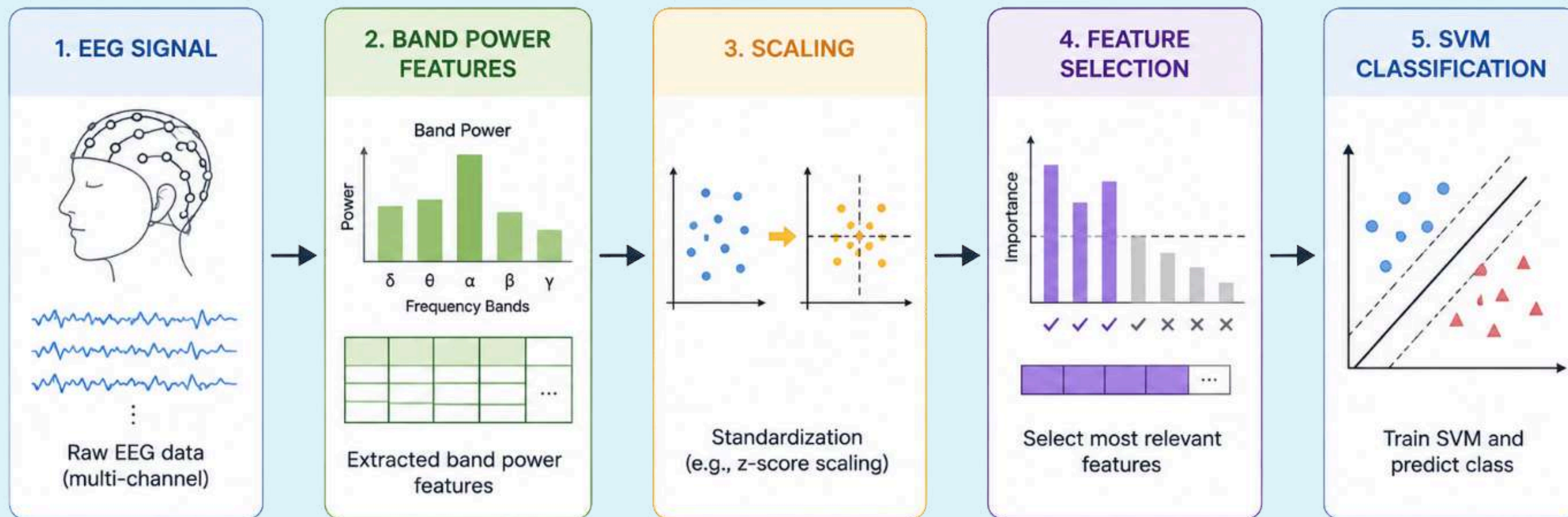
Feature Vector Size

- Common EEG channels used: 26
- Frequency bands per channel: 4
- 26 channels \times 4 frequency bands = 104 features

Thus, each EEG sample was represented as a 104-dimensional feature vector for SVM-based stroke classification.

Model-Specific Data Preparation

- Since the SVM uses numerical EEG features, feature selection was applied to retain the most useful features.
- Features were first standardized using StandardScaler.
- SelectKBest was used to select the most informative band-power features.
- The selected features were then passed to an RBF-kernel SVM classifier.

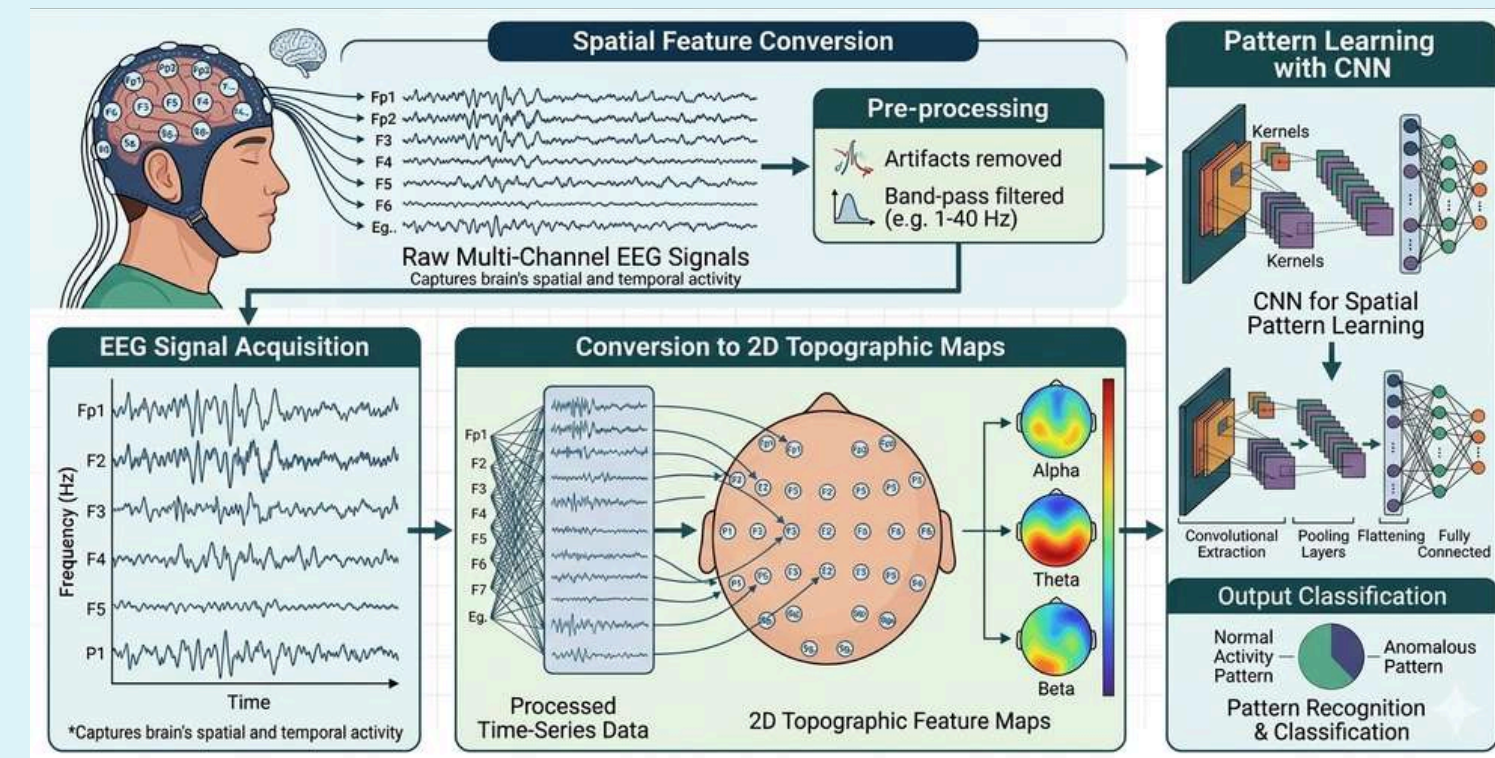


Model-Specific Data Preparation

CNN Pipeline:

- EEG signals were segmented into fixed-length windows (2 sec)* for each subject.
- Each segment was converted into a topographic brain map.
- The topomaps preserved spatial electrode information.
- No handcrafted feature vector was given to the CNN.
- The CNN automatically learned spatial patterns from the topomap images.

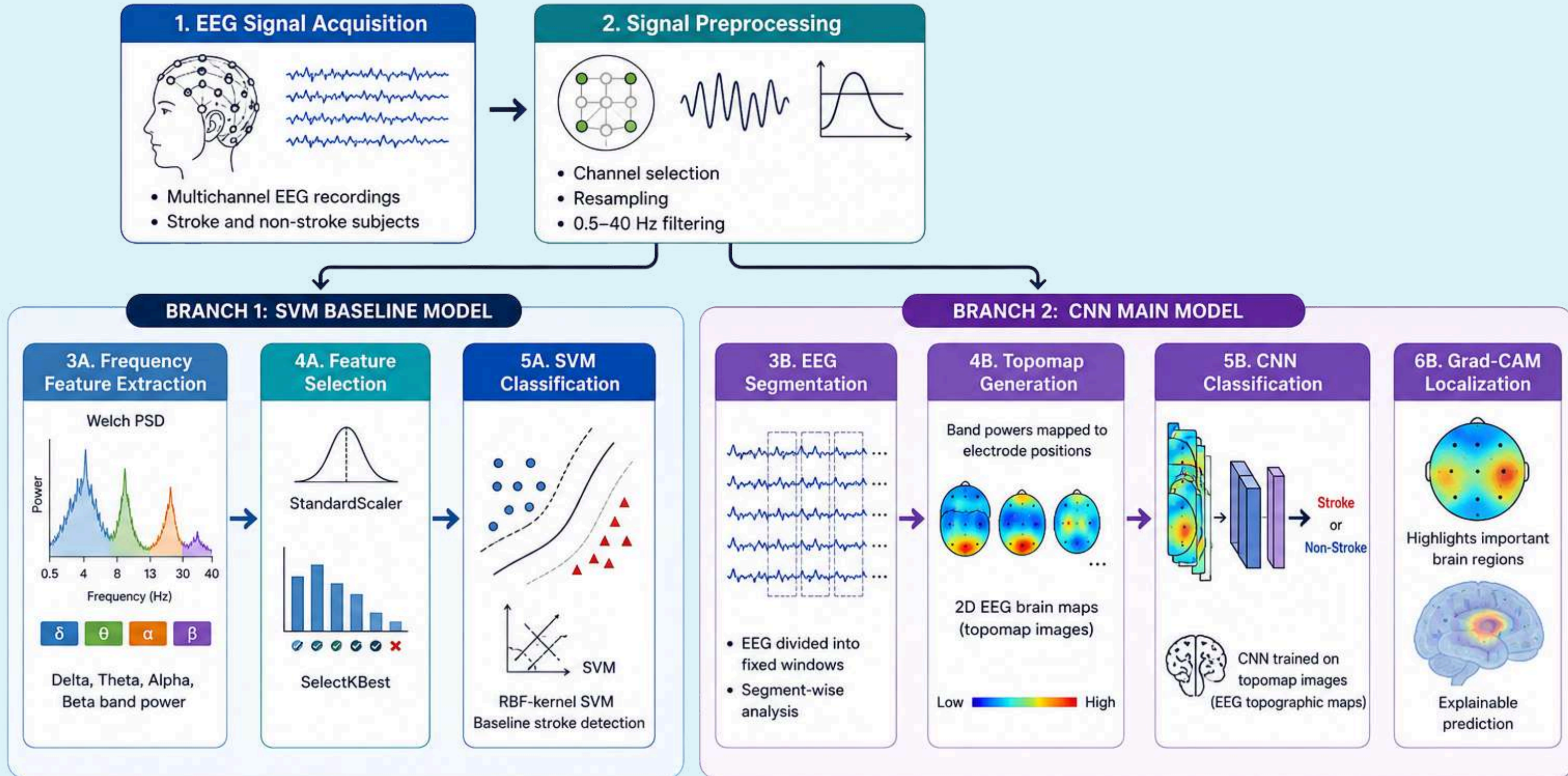
CNN learned spatial patterns directly from EEG topomap representations.



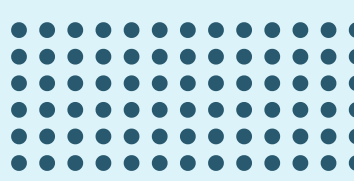
A piece of blue watercolor paper with a textured, slightly irregular edge. The paper is a medium blue color with some darker and lighter variations in tone, suggesting it was painted with watercolor. The text 'ML METHODOLOGY' is printed in a bold, black, sans-serif font, centered horizontally across the middle of the paper.

ML METHODOLOGY

ML METHODOLOGY

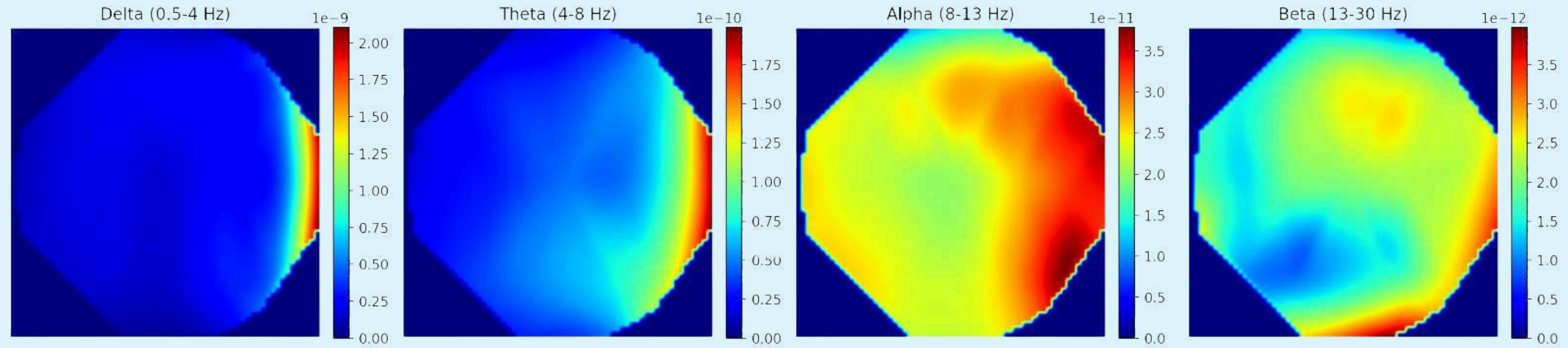


SVM was used as the baseline model with handcrafted frequency features, while **CNN** was used as the main model to learn spatial patterns from EEG topographic maps.

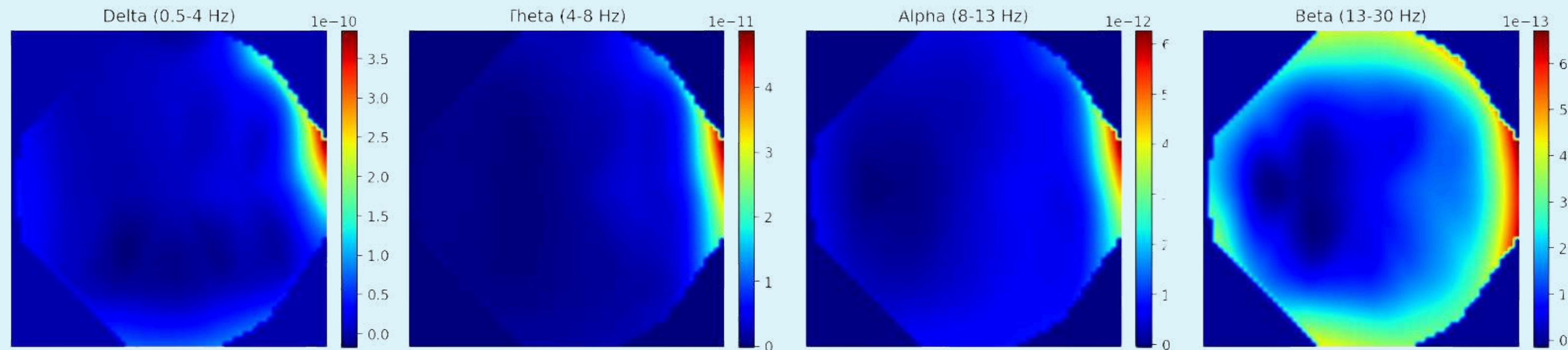


TOPOMAP GENERATION

Non-stroke subject

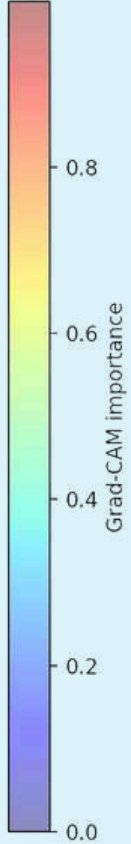
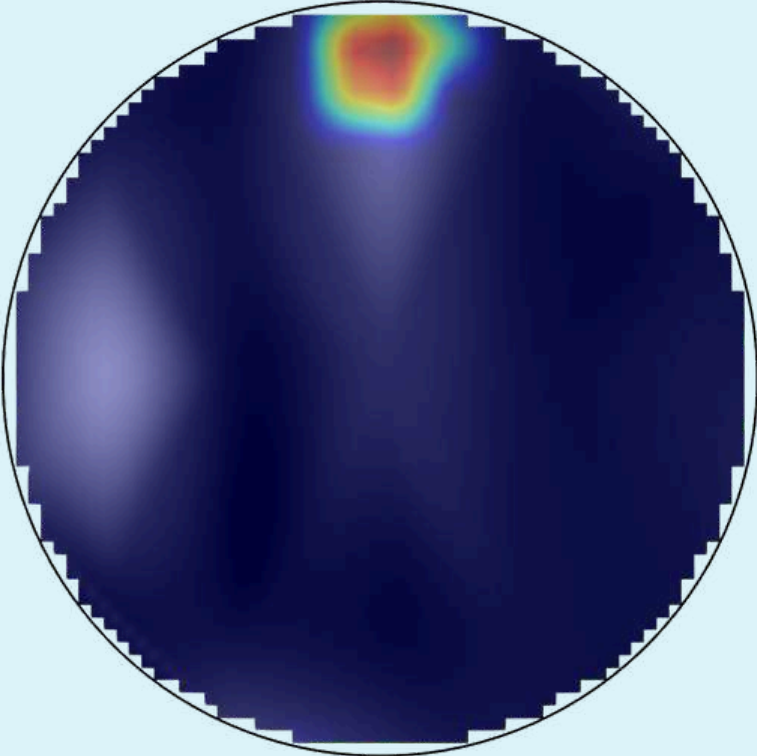


Stroke subject

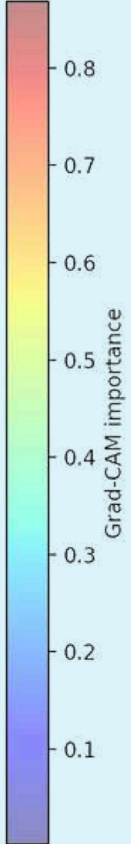
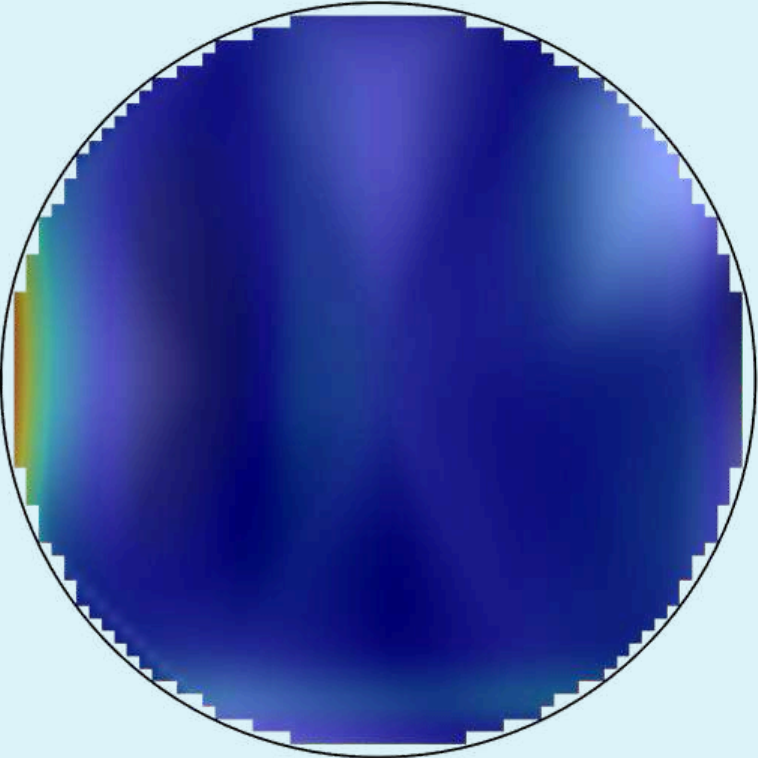


GRAD-CAM OUTPUTS

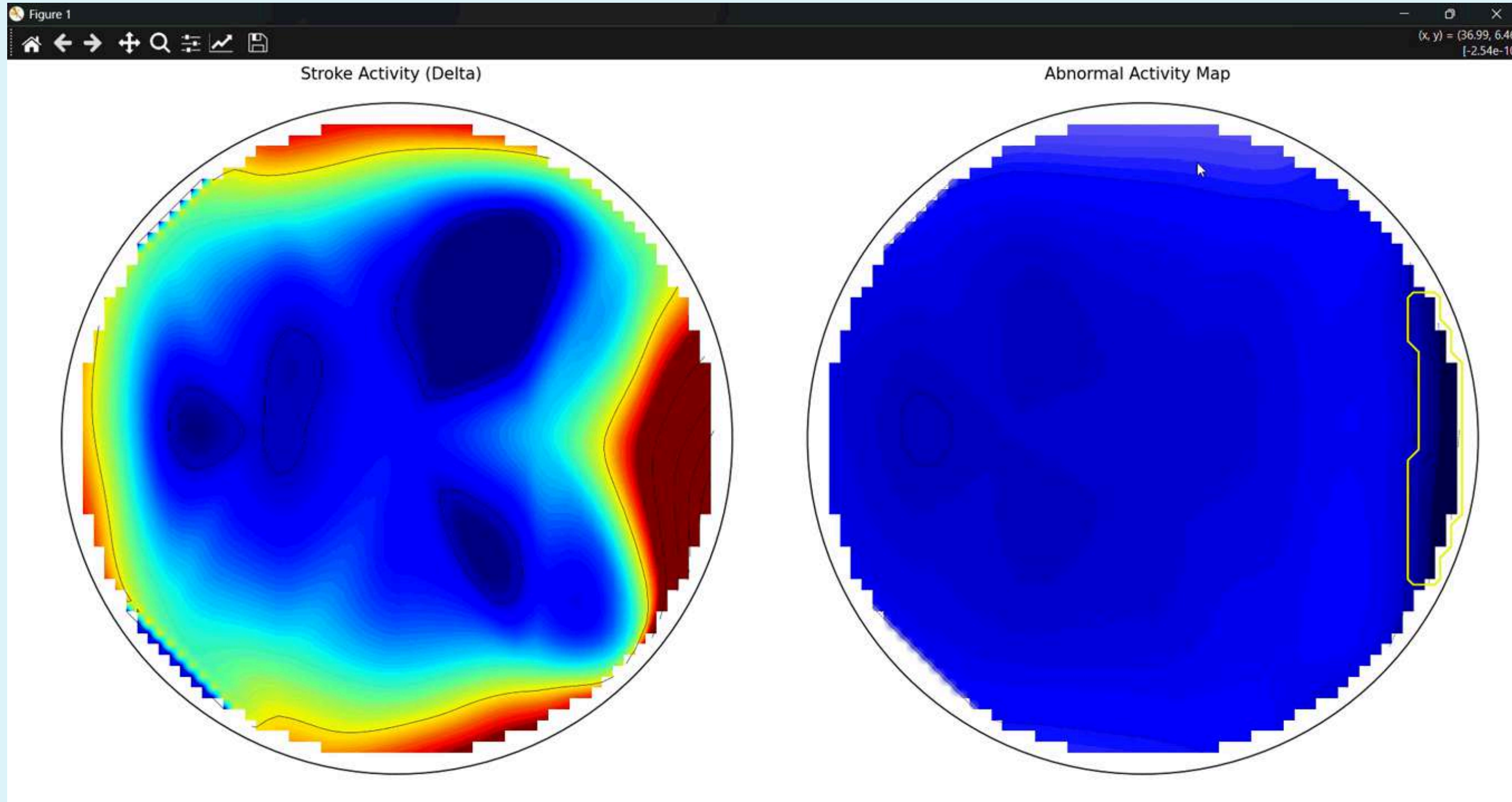
Prediction: stroke (92.98%) | Region: Midline frontal



Prediction: stroke (99.53%) | Region: Left central/temporal



LIVE TOPOMAP




[https://drive.google.com/file/d/1FhX1_ydEvvmsFEnd9BRQKK_yI-mfs_W/view?usp=drive link](https://drive.google.com/file/d/1FhX1_ydEvvmsFEnd9BRQKK_yI-mfs_W/view?usp=drive_link)



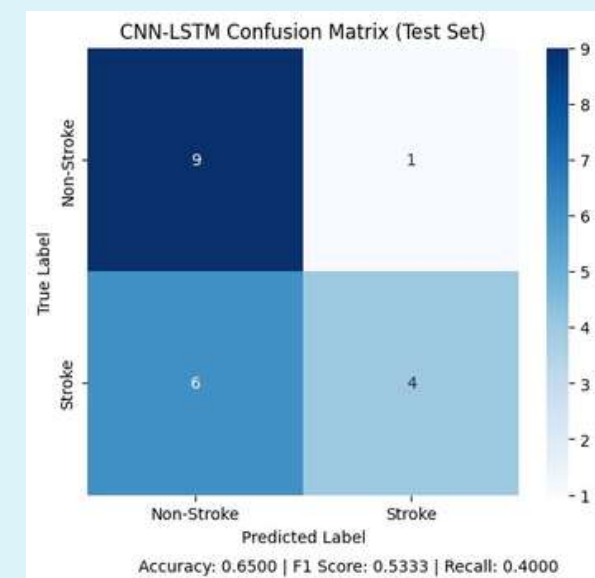
ML METHODOLOGY

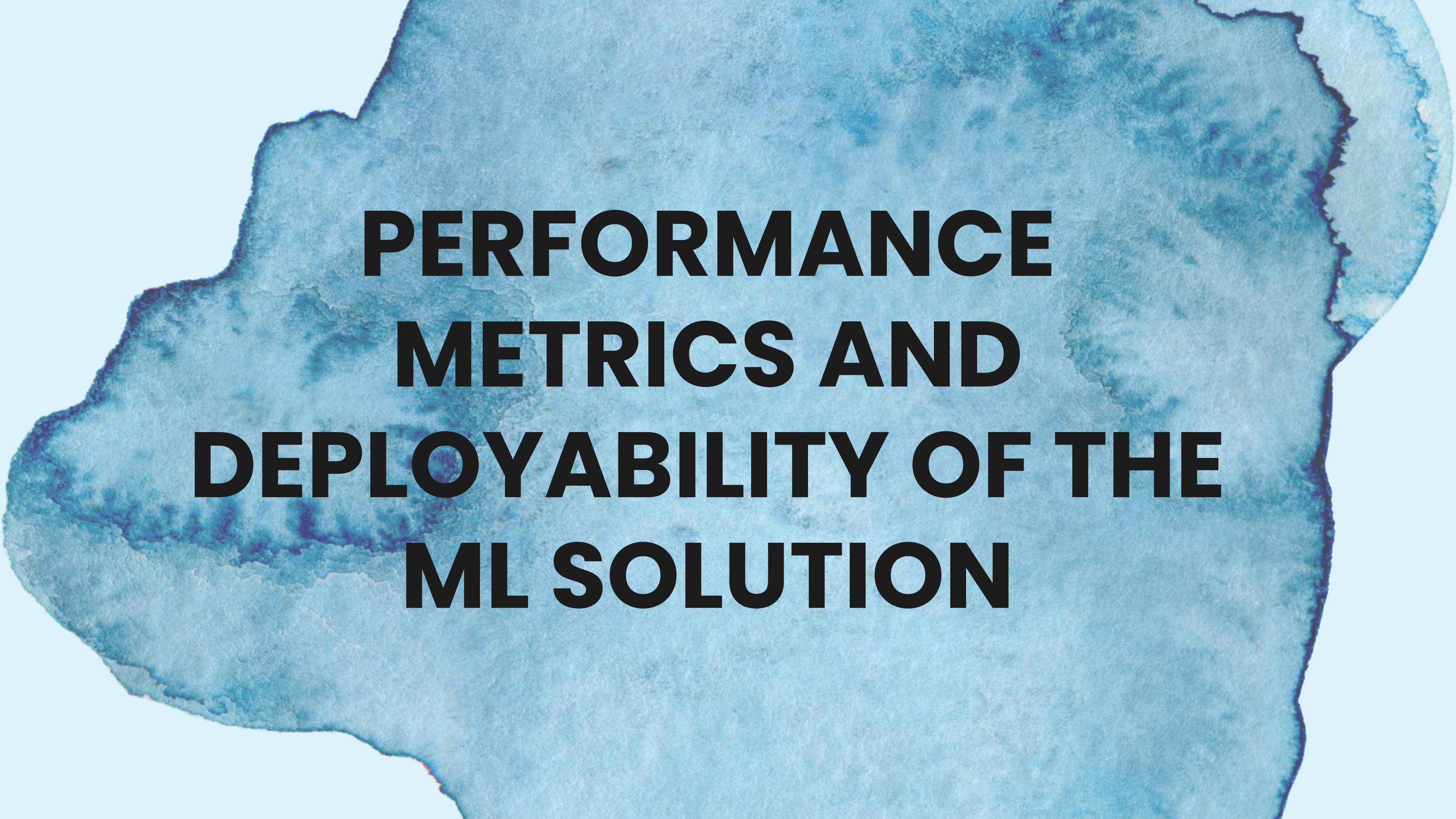
Why this approach?

- EEG captures both **frequency changes and spatial brain activity patterns**.
 - SVM was used as a **baseline** because it works well with small datasets and handcrafted features.
 - Band-power features capture stroke-related changes in Delta, Theta, Alpha, and Beta bands.
 - CNN was used because EEG topomaps convert **brain activity into image-like spatial maps**.
 - CNN learns **abnormal spatial patterns** automatically from topomap images.
 - Using SVM and CNN allows comparison between traditional ML and deep learning.
 - Grad-CAM provides **regional localization** by highlighting important brain regions.
- 

Challenge: Limited Data for CNN-LSTM

- We explored CNN-LSTM to capture both spatial and temporal EEG patterns.
- CNN was meant to learn spatial features from topomaps, while LSTM was meant to learn temporal changes across segments.
- However, the dataset had **limited independent subject-level** sequences.
- CNN-LSTM needs larger sequence-level data to generalize well.
- It showed weaker performance, especially **low stroke recall**.
- Since recall is critical for stroke detection, CNN-LSTM was not selected as the final model.
- We used CNN as the main model and SVM as the baseline due to more reliable performance.

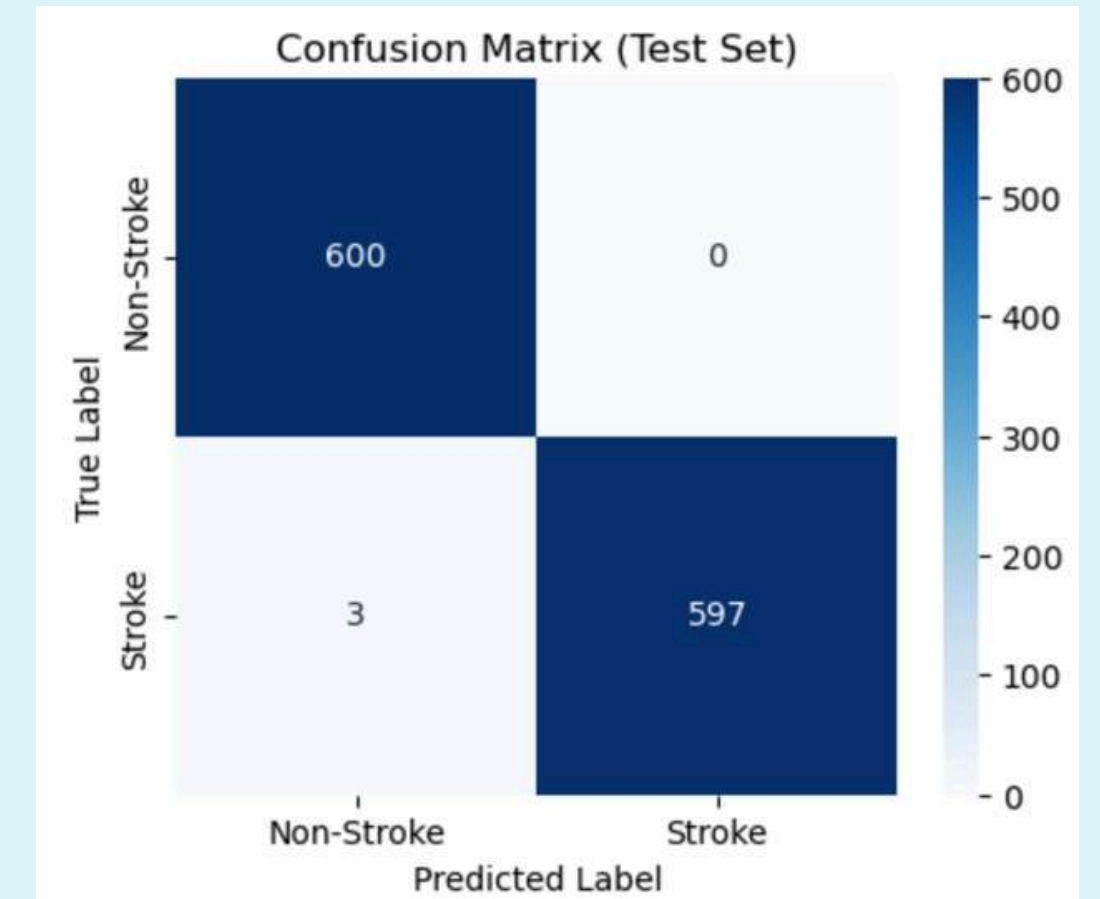
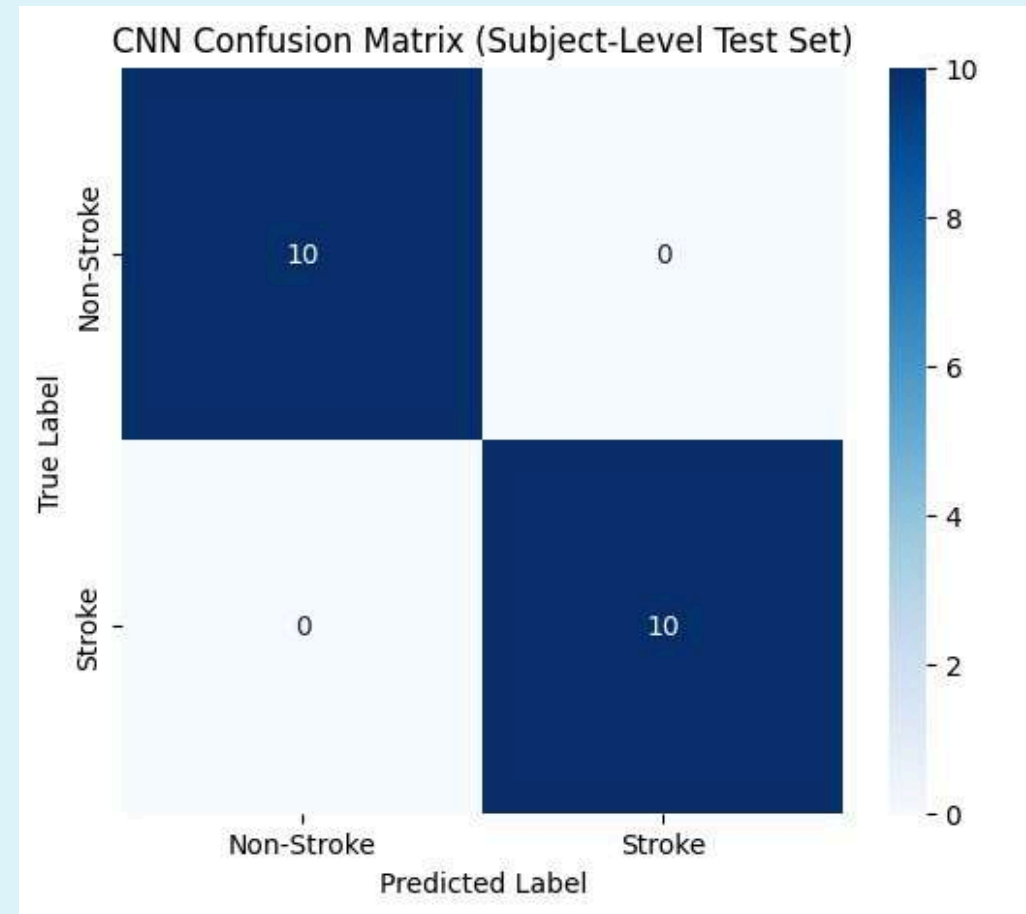
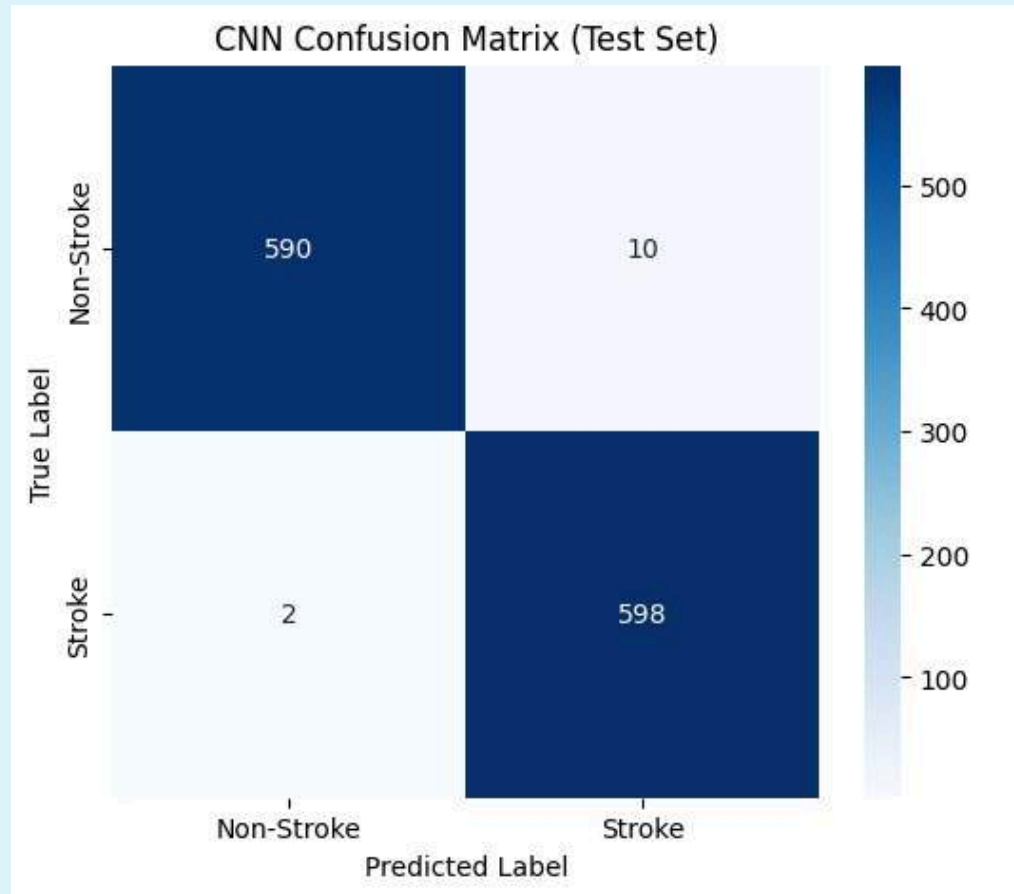




**PERFORMANCE
METRICS AND
DEPLOYABILITY OF THE
ML SOLUTION**

MODEL PERFORMANCE RESULTS:

CONFUSION MATRIX:



SVM

MODEL PERFORMANCE RESULTS:

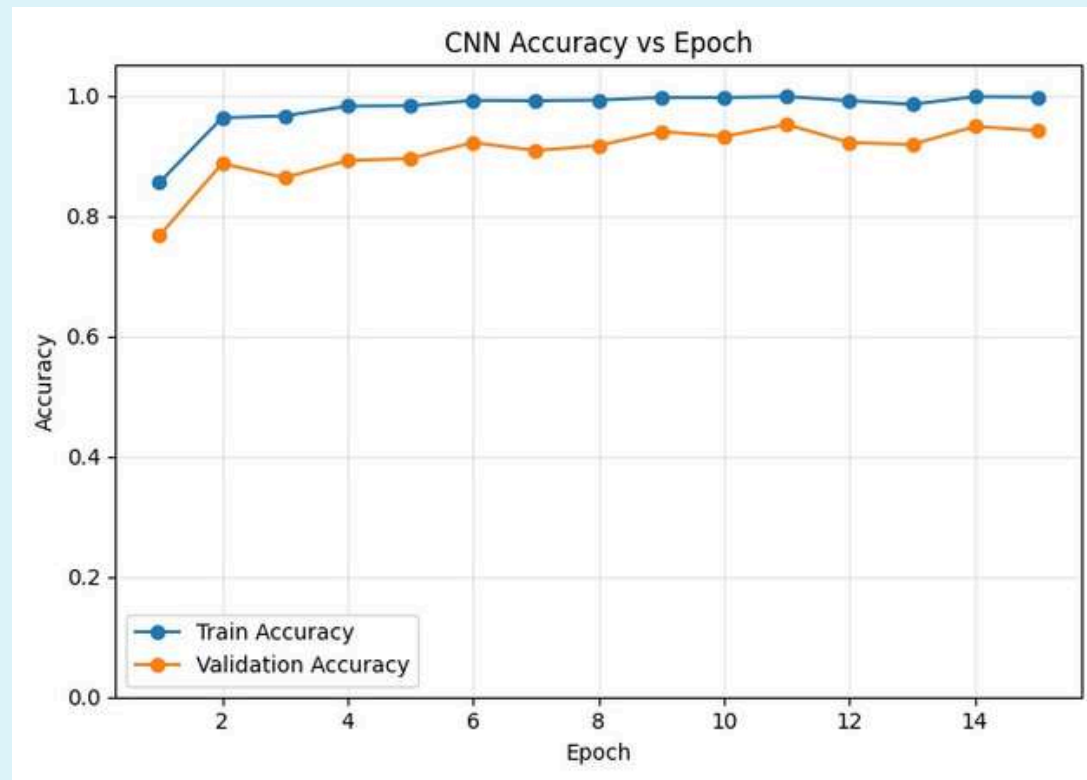
Model	Accuracy	Precision	Recall	F1-Score
SVM	0.9975	1.0	0.995	0.9975
CNN	0.99	0.9836	0.9967	0.9901
CNN-LSTM	0.75	1.0	0.5	0.6667

WHY THESE PERFORMANCE METRICS ARE SUFFICIENT FOR OUR SYSTEM

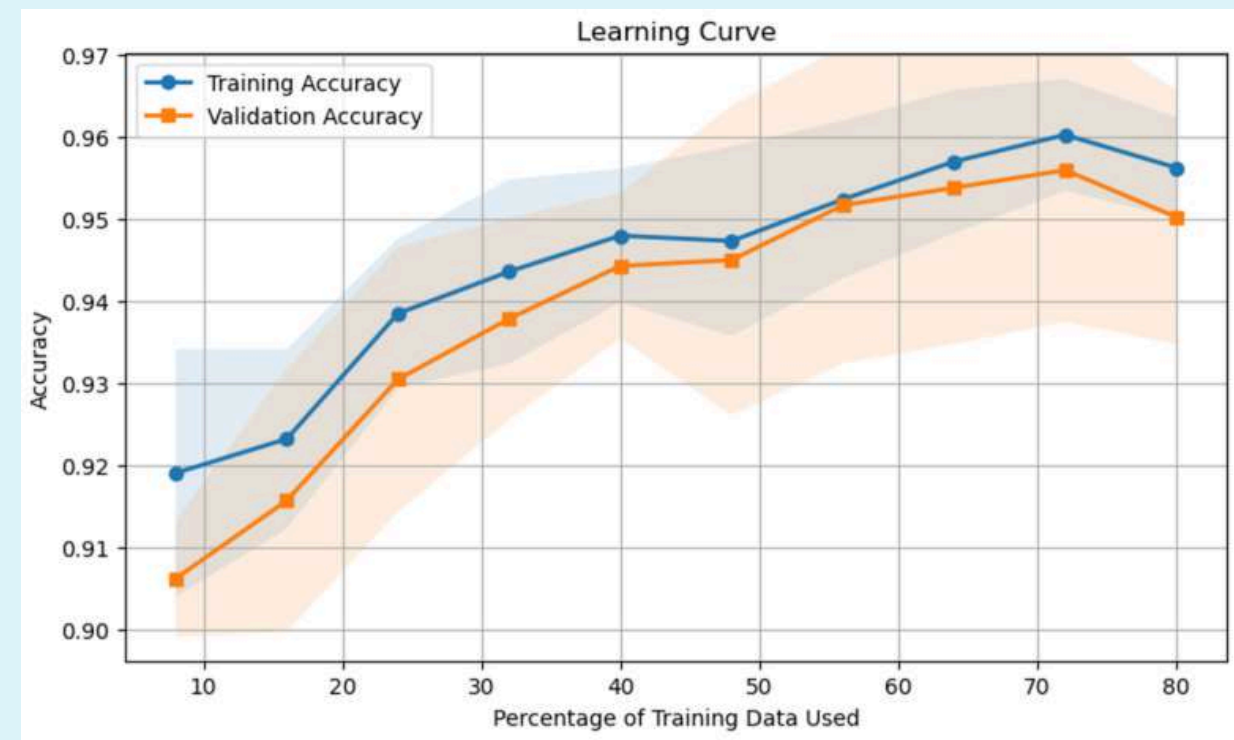
Metric / Observation	Why It Is Sufficient for Our System
SVM Performance	Achieved 99.75% accuracy and 99.75% F1-score, showing highly stable and reliable classification performance.
CNN Recall	Achieved 99.67% recall, which is critical for reducing missed stroke cases during detection.
CNN-LSTM Performance	Lower performance (75% accuracy) helped validate that spatial CNN learning was more suitable for the available EEG dataset.
Overall Evaluation	Together, accuracy, precision, recall, and F1-score sufficiently evaluate model reliability, generalization, and stroke detection capability.

MODEL PERFORMANCE RESULTS:

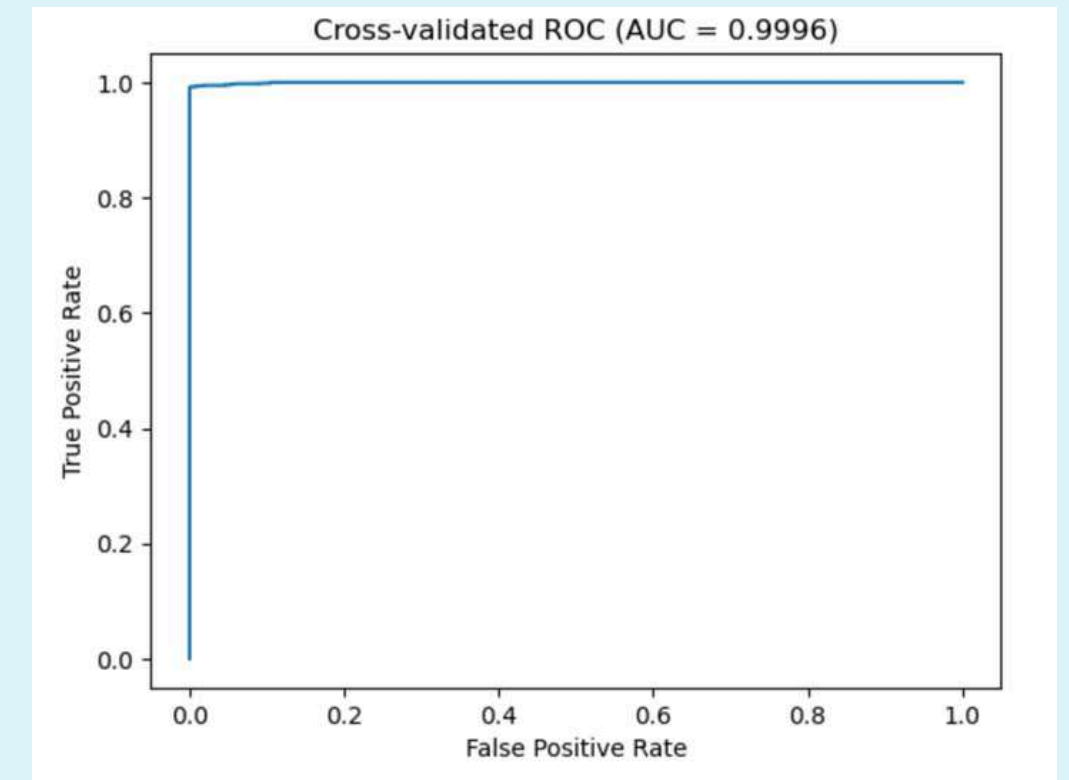
TRAIN V/S VALIDATION:



CNN



SVM



SVM

BENCHMARK COMPARISON WITH EXISTING RESEARCH

1

Existing Research Paper

- Accuracy Achieved: 86.0%
- F1-Score: 86.1%
- EEG and EOG-based ischemic stroke identification



Our Proposed CNN

- Best Performing Model: SVM
- Accuracy Achieved: 99%
- Recall: 99.67%
- F1-Score: 99.01%

BENCHMARK COMPARISON WITH EXISTING RESEARCH

2

Existing Research Paper

- Model Used: ResNet-50
- Accuracy Achieved: 90%
- EEG-based stroke classification using deep learning techniques



Our Proposed CNN

- Accuracy Achieved: 99%
- Recall: 99.67%
- F1-Score: 99.01%
- Strong classification reliability with minimal false negatives

BENCHMARK COMPARISON WITH EXISTING RESEARCH

3

Existing Research Paper

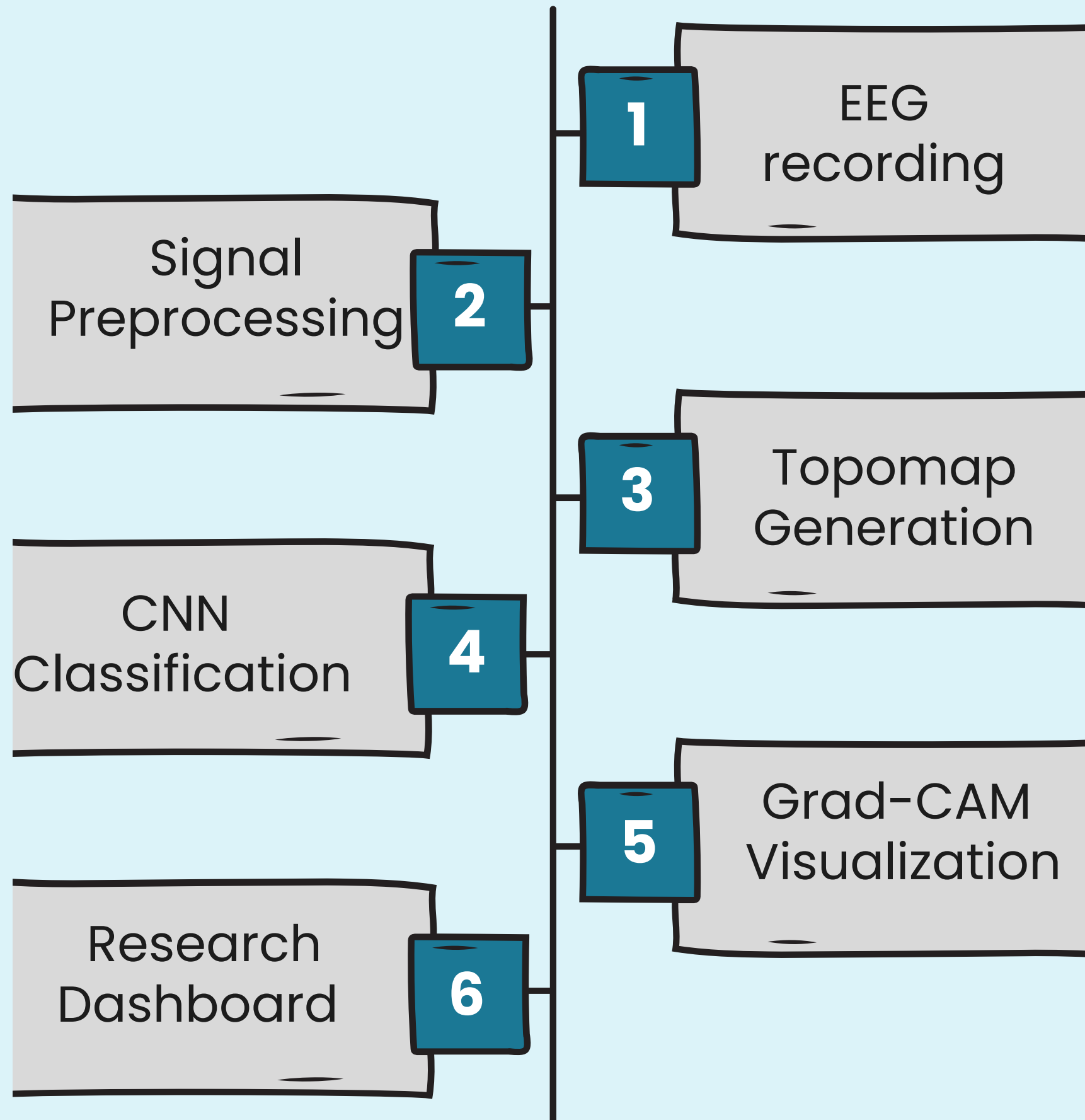
- Accuracy: 96.89%
- Precision: 96.76%
- Recall: 96.69%
- F1-Score: 96.72%
- Feature-fusion based EEG stroke analysis



Our Proposed SVM

- Accuracy: 99.75%
- F-1 Score: 99.75%
- Recall: 99.5%

DEPLOYABILITY OF THE ML SOLUTION



Possible Use at Plaksha

- Research prototype for EEG-based stroke analysis
- Screening-support tool for preliminary stroke detection
- Demonstration of EEG preprocessing and ML classification
- Laboratory experimentation for healthcare AI systems

DEPLOYMENT CHALLENGES AT SCALE



Data Variability

Different subjects and EEG devices produce varying signals



Noise & Artifacts

Eye movement and muscle activity affect EEG quality.



Real-Time Processing

Fast preprocessing and inference are needed.



Clinical Validation

Requires testing on larger medical datasets.



False Negatives

Missing stroke cases can be dangerous.



Hardware Dependency

Different EEG systems use different channel layouts.



Privacy & Consent

EEG data must be securely stored.



Generalization

Model retraining may be required for new populations.

A stylized illustration of a brain, rendered in a light blue color. The brain's surface is covered in intricate, swirling patterns of yellow and blue, resembling a marbled or abstract design. The overall style is artistic and modern. The text "Thank You" is centered over the brain.

Thank You