**Sylhet Engineering College**

**Department of Computer Science & Engineering**

**Shahjalal University of Science and Technology**

# "EEG-Based Comparison of Brain Activity: Normal Conditions Versus Smartphone Typing and Scrolling"

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22 july,2025

# Recommendation Letter from Thesis Supervisor

The thesis entitled "**EEG-Based Comparison of Brain Activity: Normal Conditions Versus Smartphone Typing and Scrolling**" submitted by the group as mentioned below has been accepted as satisfactory in partial fulfilment of the requirements for the degree B. Sc. in Computer Science and Engineering in July, 2025.

Group Members:

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Date: 22 July,2025

# Certificate of Acceptance of the Thesis

The thesis is titled **“EEG-Based Comparison of Brain Activity: Normal Conditions Versus Smartphone Typing and Scrolling”** submitted by **Bithi Rani Kapali** and **Md. Maruf Ahmed**; Student ID. **2019331505** and **2019331552**; Session **2019-20**, to the Department of Computer Science and Engineering , Sylhet Engineering College, has been accepted as satisfactory in partial fulfilment of the requirement for the Degree of Bachelor of Science in Computer Science and Engineering and approved as to its style and contents.

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# Contents

## List of Figures

## List of Tables

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# Abstract

The proliferation of smartphones has made activities like typing and scrolling integral to daily life, yet the specific cognitive load they impose remains underexplored. This study presents an EEG-based comparison of brain activity during normal resting conditions versus smartphone typing and scrolling to quantify these neural differences. Multi-channel EEG data was used as a baseline for a 'normal' state. A novel data simulation methodology was developed to generate distinct datasets for 'typing' and 'scrolling' states by modulating the power of specific frequency bands (Alpha and Beta) using Fast Fourier Transform (FFT), reflecting established neuroscientific principles of cognitive and motor engagement.

The methodology follows a structured EEG processing pipeline: raw EEG CSV files are preprocessed to retain key brain channels, then filtered using a Butterworth filter. Frequency-domain features are extracted using Welch's method. These features are used to train and evaluate models like Conv1D, LSTM, and CNN-LSTM hybrids. PCA, t-SNE, topographical map and PSD (Power Spectral Density) are applied for dimensionality reduction and data visualization.

Expected key findings include observable and quantifiable differences in brainwave patterns (e.g., alpha, beta, theta activity) across the three conditions. The classification models are expected to demonstrate significant accuracy in distinguishing between these states based on the extracted EEG features.

In conclusion, this research aims to provide empirical evidence for the impact of common smartphone activities on brain function. The findings will contribute to a deeper understanding of the neural correlates of digital interaction, offering insights into potential implications for cognitive load, attention, and overall brain health in the context of pervasive smartphone use.

**Keywords:** EEG, Signal Processing, Filtering, Butterworth, PSD, Welch, CNN, LSTM, CNN-LSTM, Deep Learning, Classification, Brain Activity, Feature Extraction, Frequency Domain, PCA, t-SNE, Neural Networks.

# Introduction

## 1.1 **Background**

In recent years, the pervasive use of smartphones has brought significant changes to human behavior, communication patterns, and cognitive engagement. Activities such as typing and scrolling on smartphones have become deeply integrated into daily life, often performed for extended periods without conscious awareness. Despite the convenience and efficiency of these interactions, growing concerns have emerged regarding their cognitive and neurological impact, especially with prolonged or repetitive use.

Electroencephalography (EEG), a non-invasive method for recording electrical activity in the brain, offers a powerful approach for studying the neural dynamics associated with such digital interactions. EEG allows for the real-time monitoring of brainwave patterns, providing valuable insights into attention, motor planning, cognitive load, and emotional responses. This makes it particularly suitable for investigating how the brain responds under different behavioral states.

This research focuses on a comparative analysis of brain activity across three specific conditions: resting (normal baseline), smartphone typing, and smartphone scrolling. By analyzing EEG signals during these activities, we aim to identify distinct neural patterns and quantify changes in brainwave activity that may correspond to varying levels of attention, motor engagement, and cognitive processing.

The motivation for this study lies in the intersection of neuroscience and human-computer interaction. As digital device usage continues to rise, it becomes increasingly important to understand the neurophysiological effects of routine smartphone activities. Such knowledge not only enhances our understanding of brain-computer interface (BCI) systems but also contributes to broader areas such as digital health, cognitive ergonomics, and the design of attention-aware technologies.

## 1.2 Problem Statement

In the modern digital age, smartphone usage has become deeply embedded in daily human activity, significantly altering patterns of cognitive and neural engagement. While extensive research has been conducted on brain activity in controlled or resting conditions, there is a noticeable lack of comparative studies that analyze how everyday interactions such as typing and scrolling on smartphones impact brain function. These common activities may induce subtle but important variations in cognitive load and attention, which can be captured through electroencephalography (EEG).

However, due to limitations in publicly available real-world datasets, especially EEG recordings specifically labeled for smartphone typing and scrolling tasks, researchers often face challenges in conducting accurate comparative analyses. This scarcity of labeled data, combined with the complexity of EEG signal interpretation, makes it difficult to understand the brain’s behavioral patterns during these real-life scenarios.

Thus, there is a pressing need for a structured EEG-based comparative study that can effectively analyze brain activity differences among normal resting, smartphone typing, and smartphone scrolling conditions, using deep learning models to identify meaningful patterns. This study aims to fill that research gap by developing a robust methodology to classify and interpret these cognitive states using preprocessed EEG data.

## 1.3 Objectives

The following are the main goals of this studies:

- Compare EEG Signals: Resting vs. smartphone typing & scrolling.
- Examine Brain Activity: Changes during smartphone interactions.
- Assess Cognitive Load: Attention in smartphone tasks.
- Evaluate Motor Cortex: Activation in smartphone typing.
- Offer Insights: Reduce cognitive strain in smartphone interfaces.

## 1.4 Scope and Limitations

This study focuses on classifying simulated EEG data derived from a baseline of normal brain activity. The simulation exaggerates the differences in Alpha and Beta wave power to test the model's maximum potential under clearly defined conditions. The findings are based on a specific set of 19 EEG channels and a limited number of subjects from the initial dataset. The results demonstrate the feasibility of the classification approach but would require testing on a larger, more diverse dataset of real-time, event-marked EEG recordings for clinical or commercial application.

Despite promising results, the study has several limitations:

- **Simulated Data for Task Conditions**: Typing and scrolling EEG signals were generated due to practical data collection constraints, which may not fully capture the neural dynamics of real usage.
- **Sample Diversity**: The resting EEG data was collected from a limited number of individuals, potentially affecting generalizability.
- **Environment Control**: The EEG data was not collected in a tightly controlled environment, and variations in mental state may have influenced results.

Despite these limitations, the study provides a valuable foundation for future research into the neural effects of digital behavior and highlights the potential of EEG in understanding cognitive responses to technology interaction.

# Literature Review

## 2.1 Existing Research on EEG and Cognitive Load

Electroencephalography (EEG) has been widely used to study brain activity and cognitive load due to its non-invasive nature and high temporal resolution. EEG signals are often analyzed to detect mental workload, attention, and engagement during various tasks. Studies have shown that specific frequency bands, such as alpha (8–13 Hz), beta (13–30 Hz), and theta (4–7 Hz), are strongly correlated with different cognitive states. For example, decreased alpha activity is commonly associated with increased attention, while heightened theta activity may indicate cognitive effort or memory processing. Researchers have used EEG to measure brain responses during tasks such as mental arithmetic, working memory challenges, and reading comprehension, effectively linking EEG markers to levels of cognitive load.

## 2.2 Related Works

Several studies have used machine learning and deep learning models to classify EEG signals based on cognitive states or task engagement. For instance, CNNs (Convolutional Neural Networks) and LSTMs (Long Short-Term Memory networks) have been employed to detect mental fatigue, drowsiness, and attention shifts with high accuracy. Projects like DEAP and SEED have explored emotional states using EEG, while datasets like PhysioNet provide mental task classification data. Yet, these works often focus on well-defined laboratory conditions and do not address common digital activities like smartphone use. Some research has attempted to detect attention loss during screen use or cognitive load in educational settings, but these lack a direct comparison between real-world smartphone interactions and resting states.

## 2.3 Identified Research Gaps

**Thesis paper-1:**

**Title: Using EEG to Distinguish between Writing and Typing for the same Cognitive Task.**

**Authors: Xiaodong Qu, Qingtian Mei, Peiyan Liu and Timothy Hickey.**

**Findings:**

- EEG signals distinguish cognitive tasks (e.g., reading, typing) with 70% accuracy within sessions and 44% across sessions.
- Machine learning (Random Forest, LSTM, CNN, SVM) effectively classifies brain activity patterns for different tasks.
- Motor cortex activation varies between typing and writing, indicating unique neural signatures for input methods.
- Task transitions require 12-18 seconds for stable brain activity adaptation.
- Absolute Band Powers (BP) in EEG signals reveal motor-related and cognitive workload differences across tasks.

**Thesis paper-2:**

**Title: EEG Signal Analysis of Writing and Typing between Adults with Dyslexia and Normal Controls.**

**Authors: Harshani Perera, Mohd Fairuz Shiratuddin.**

**Findings:**

- EEG Classification – kNN (92.81% accuracy) outperforms LDA in classifying EEG signals.
- Frontal & Central Brain Regions – Key EEG channels (F5, F3, Fz, F4, F6) are crucial for typing analysis.
- Key Brain Regions – F3 and F4 frontal channels play a crucial role in EEG-based typing analysis.

**Thesis paper-3:**

**Title: Effect of Smartphone Distractions on Cognitive Performance in Adolescents.**

**Authors: T. A Suhail, K.P Indiradevi.**

**Findings:**

- 600 healthy adolescents from South India, 50.91% high smartphone users.
- High smartphone use linked to performance decline, sleep disturbances, and mental stress.
- Significant drop in cognitive performance indices after smartphone use.
- Multitasking or switching between learning and phone use impairs cognitive functions.
- Smartphone distractions adversely affect cognitive performance in adolescents.

# Methodology

## 3.1 Overview of Approach

This study aims to perform a comparative analysis of brain activity under three conditions: resting**,** smartphone typing**,** and smartphone scrolling**,** using EEG data. Resting-state EEG signals were collected from real human subjects in a hospital environment. Since acquiring EEG data during actual smartphone interactions posed logistical and ethical challenges, typing and scrolling conditions were simulated from the real resting signals using biologically plausible signal modulations.

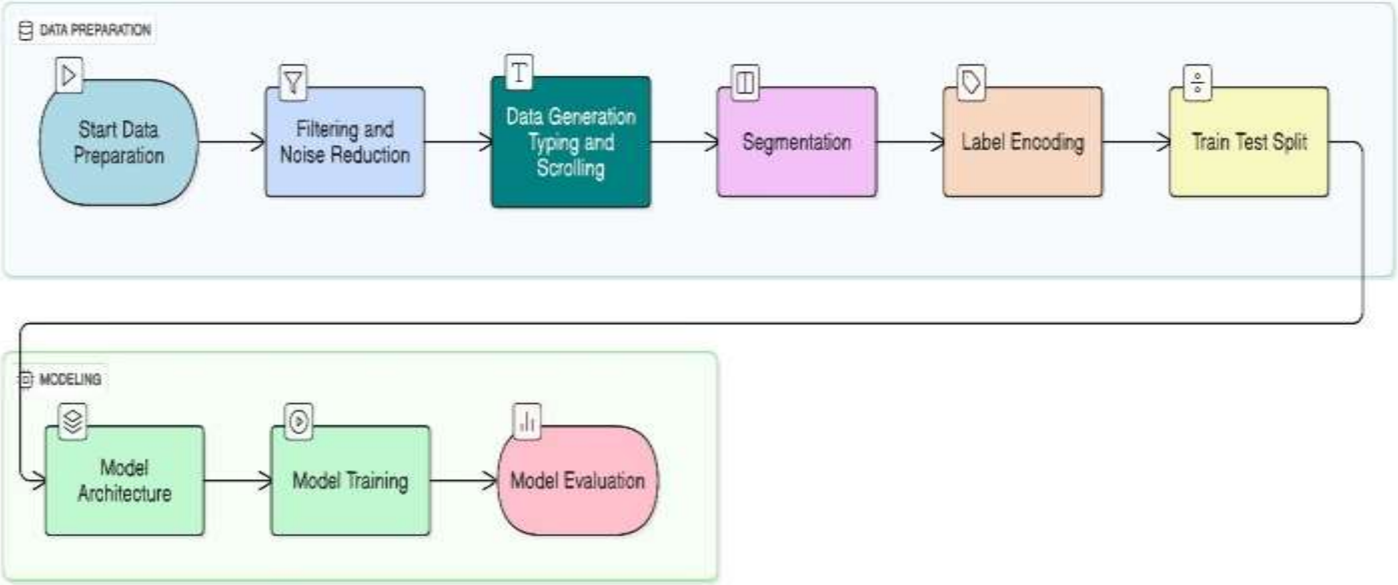
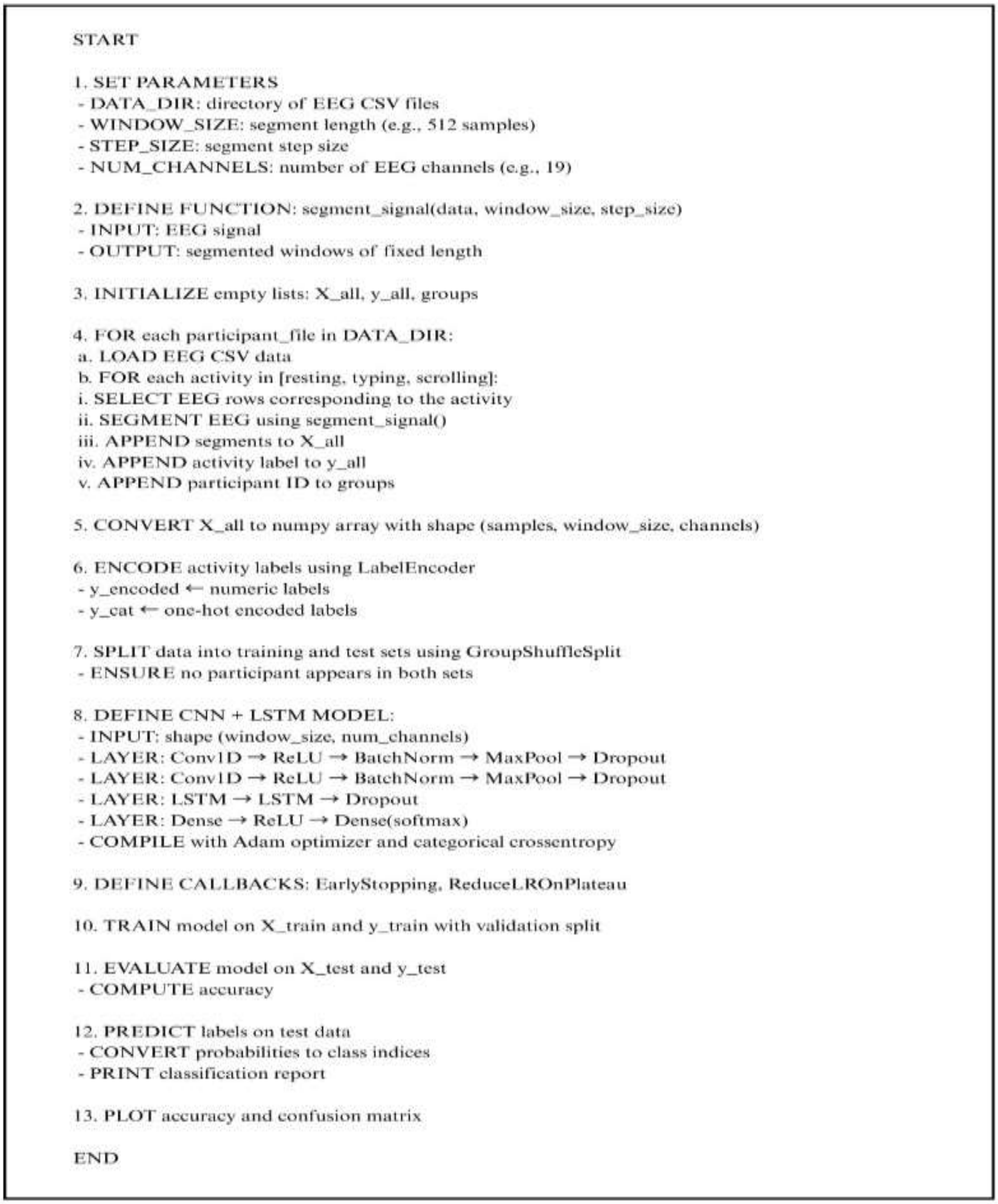


*Figure 1: Workflow Diagram*

The overall pipeline includes:

- Collecting and preprocessing real resting-state EEG signals
- Simulating typing and scrolling EEG using signal modulation techniques
- Segmenting the data into short windows for temporal modeling
- Training a deep learning model combining CNN and LSTM to classify the three mental states
- Evaluating the model with a group-based split to ensure no data leakage between training and testing.

## Workflow for EEG Activity Classification using CNN-LSTM:

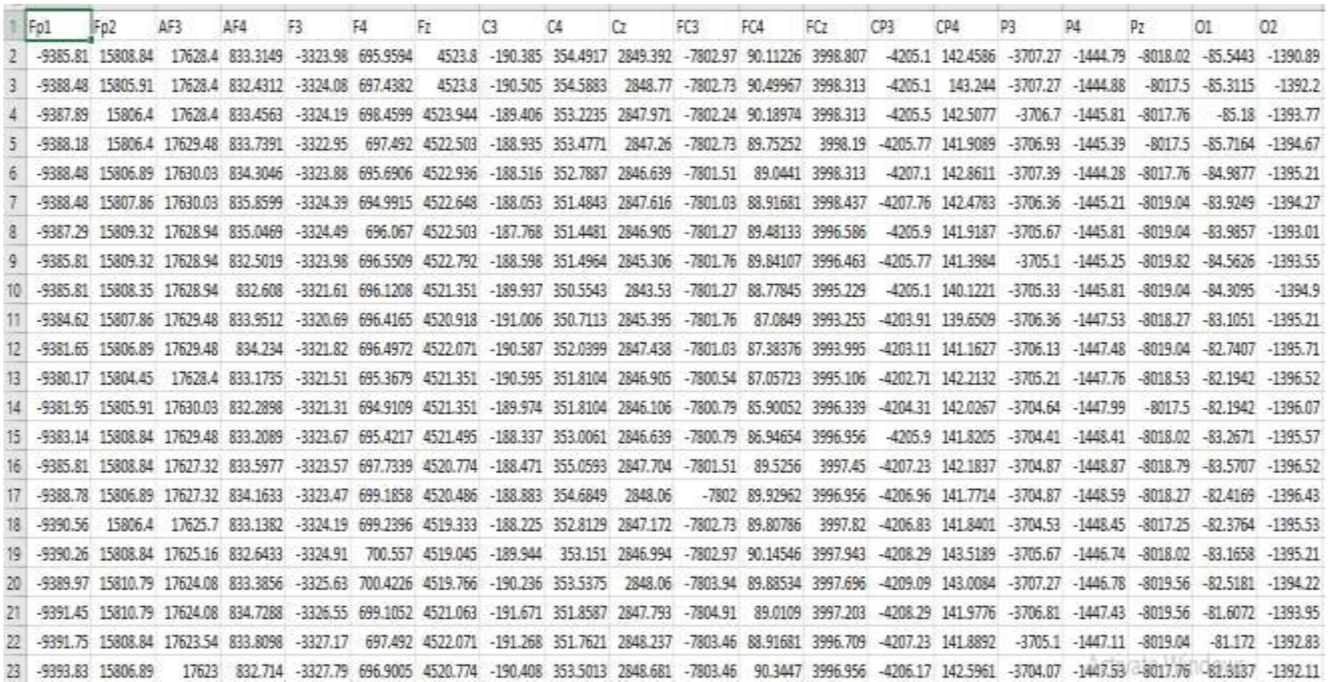


```
START

1. SET PARAMETERS
 - DATA_DIR: directory of EEG CSV files
 - WINDOW_SIZE: segment length (e.g., 512 samples)
 - STEP_SIZE: segment step size
 - NUM_CHANNELS: number of EEG channels (e.g., 19)

2. DEFINE FUNCTION: segment_signal(data, window_size, step_size)
 - INPUT: EEG signal
 - OUTPUT: segmented windows of fixed length

3. INITIALIZE empty lists: X_all, y_all, groups

4. FOR each participant_file in DATA_DIR:
 a. LOAD EEG CSV data
 b. FOR each activity in [resting, typing, scrolling]:
 i. SELECT EEG rows corresponding to the activity
 ii. SEGMENT EEG using segment_signal()
 iii. APPEND segments to X_all
 iv. APPEND activity label to y_all
 v. APPEND participant ID to groups

5. CONVERT X_all to numpy array with shape (samples, window_size, channels)

6. ENCODE activity labels using LabelEncoder
 - y_encoded ← numeric labels
 - y_cat ← one-hot encoded labels

7. SPLIT data into training and test sets using GroupShuffleSplit
 - ENSURE no participant appears in both sets

8. DEFINE CNN + LSTM MODEL:
 - INPUT: shape (window_size, num_channels)
 - LAYER: Conv1D → ReLU → BatchNorm → MaxPool → Dropout
 - LAYER: Conv1D → ReLU → BatchNorm → MaxPool → Dropout
 - LAYER: LSTM → LSTM → Dropout
 - LAYER: Dense → ReLU → Dense(softmax)
 - COMPILE with Adam optimizer and categorical crossentropy

9. DEFINE CALLBACKS: EarlyStopping, ReduceLROnPlateau

10. TRAIN model on X_train and y_train with validation split

11. EVALUATE model on X_test and y_test
 - COMPUTE accuracy

12. PREDICT labels on test data
 - CONVERT probabilities to class indices
 - PRINT classification report

13. PLOT accuracy and confusion matrix

END
```

## 3.2 Dataset Description

The dataset comprises EEG recordings from 26 human participants, collected in a hospital under resting conditions using the standard 10–20 electrode montage. Each recording:

- Contains 64 EEG channels
- Is sampled at 256 Hz
- Has a total duration of approximately 2 minutes for each task per subject



| 1 | Fp1 | Fp2 | AF3 | AF4 | F3 | F4 | Fz | C3 | C4 | Cz | FC3 | FC4 | FCz | CP3 | CP4 | P3 | P4 | Pz | O1 | O2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | -9385.81 | 15808.84 | 17628.4 | 833.3149 | -3323.98 | 695.9594 | 4523.8 | -190.385 | 354.4917 | 2849.392 | -7802.97 | 90.11226 | 3998.807 | -4205.1 | 142.4586 | -3707.27 | -1444.79 | -8018.02 | -85.5443 | -1390.89 |
| 3 | -9388.48 | 15805.91 | 17628.4 | 832.4312 | -3324.08 | 697.4382 | 4523.8 | -190.505 | 354.5883 | 2848.77 | -7802.73 | 90.49967 | 3998.313 | -4205.1 | 143.244 | -3707.27 | -1444.88 | -8017.5 | -85.3115 | -1392.2 |
| 4 | -9387.89 | 15806.4 | 17628.4 | 833.4563 | -3324.19 | 698.4599 | 4523.944 | -189.406 | 353.2235 | 2847.971 | -7802.24 | 90.18974 | 3998.313 | -4205.5 | 142.5077 | -3706.7 | -1445.81 | -8017.76 | -85.18 | -1393.77 |
| 5 | -9388.18 | 15806.4 | 17629.48 | 833.7391 | -3322.95 | 697.492 | 4522.503 | -188.935 | 353.4771 | 2847.26 | -7802.73 | 89.75252 | 3998.19 | -4205.77 | 141.9089 | -3706.93 | -1445.39 | -8017.5 | -85.7164 | -1394.67 |
| 6 | -9388.48 | 15806.89 | 17630.03 | 834.3046 | -3323.88 | 695.6906 | 4522.936 | -188.516 | 352.7887 | 2846.639 | -7801.51 | 89.0441 | 3998.313 | -4207.1 | 142.8611 | -3707.39 | -1444.28 | -8017.76 | -84.9877 | -1395.21 |
| 7 | -9388.48 | 15807.86 | 17630.03 | 835.8599 | -3324.39 | 694.9915 | 4522.648 | -188.053 | 351.4843 | 2847.616 | -7801.03 | 88.91681 | 3998.437 | -4207.76 | 142.4783 | -3706.36 | -1445.21 | -8019.04 | -83.9249 | -1394.27 |
| 8 | -9387.29 | 15809.32 | 17628.94 | 835.0469 | -3324.49 | 696.067 | 4522.503 | -187.768 | 351.4481 | 2846.905 | -7801.27 | 89.48133 | 3996.586 | -4205.9 | 141.9187 | -3705.67 | -1445.81 | -8019.04 | -83.9857 | -1393.01 |
| 9 | -9385.81 | 15809.32 | 17628.94 | 832.5019 | -3323.98 | 696.5509 | 4522.792 | -188.598 | 351.4964 | 2845.306 | -7801.76 | 89.84107 | 3996.463 | -4205.77 | 141.3984 | -3705.1 | -1445.25 | -8019.82 | -84.5626 | -1393.55 |
| 10 | -9385.81 | 15808.35 | 17628.94 | 832.608 | -3321.61 | 696.1208 | 4521.351 | -189.937 | 350.5543 | 2843.53 | -7801.27 | 88.77845 | 3995.229 | -4205.1 | 140.1221 | -3705.33 | -1445.81 | -8019.04 | -84.3095 | -1394.9 |
| 11 | -9384.62 | 15807.86 | 17629.48 | 833.9512 | -3320.69 | 696.4165 | 4520.918 | -191.006 | 350.7113 | 2845.395 | -7801.76 | 87.0849 | 3993.255 | -4203.91 | 139.6509 | -3706.36 | -1447.53 | -8018.27 | -83.1051 | -1395.21 |
| 12 | -9381.65 | 15806.89 | 17629.48 | 834.234 | -3321.82 | 696.4972 | 4522.071 | -190.587 | 352.0399 | 2847.438 | -7801.03 | 87.38376 | 3993.995 | -4203.11 | 141.1627 | -3706.13 | -1447.48 | -8019.04 | -82.7407 | -1395.71 |
| 13 | -9380.17 | 15804.45 | 17628.4 | 833.1735 | -3321.51 | 695.3679 | 4521.351 | -190.595 | 351.8104 | 2846.905 | -7800.54 | 87.05723 | 3995.106 | -4202.71 | 142.2132 | -3705.21 | -1447.76 | -8018.53 | -82.1942 | -1396.52 |
| 14 | -9381.95 | 15805.91 | 17630.03 | 832.2898 | -3321.31 | 694.9109 | 4521.351 | -189.974 | 351.8104 | 2846.106 | -7800.79 | 85.90052 | 3996.339 | -4204.31 | 142.0267 | -3704.64 | -1447.99 | -8017.5 | -82.1942 | -1396.07 |
| 15 | -9383.14 | 15808.84 | 17629.48 | 833.2089 | -3323.67 | 695.4217 | 4521.495 | -188.337 | 353.0061 | 2846.639 | -7800.79 | 86.94654 | 3996.956 | -4205.9 | 141.8205 | -3704.41 | -1448.41 | -8018.02 | -83.2671 | -1395.57 |
| 16 | -9385.81 | 15808.84 | 17627.32 | 833.5977 | -3323.57 | 697.7339 | 4520.774 | -188.471 | 355.0593 | 2847.704 | -7801.51 | 89.5256 | 3997.45 | -4207.23 | 142.1837 | -3704.87 | -1448.87 | -8018.79 | -83.5707 | -1396.52 |
| 17 | -9388.78 | 15806.89 | 17627.32 | 834.1633 | -3323.47 | 699.1858 | 4520.486 | -188.883 | 354.6849 | 2848.06 | -7802 | 89.92962 | 3996.956 | -4206.96 | 141.7714 | -3704.87 | -1448.59 | -8018.27 | -82.4169 | -1396.43 |
| 18 | -9390.56 | 15806.4 | 17625.7 | 833.1382 | -3324.19 | 699.2396 | 4519.333 | -188.225 | 352.8129 | 2847.172 | -7802.73 | 89.80786 | 3997.82 | -4206.83 | 141.8401 | -3704.53 | -1448.45 | -8017.25 | -82.3764 | -1395.53 |
| 19 | -9390.26 | 15808.84 | 17625.16 | 832.6433 | -3324.91 | 700.557 | 4519.045 | -189.944 | 353.151 | 2846.994 | -7802.97 | 90.14546 | 3997.943 | -4208.29 | 143.5189 | -3705.67 | -1446.74 | -8018.02 | -83.1658 | -1395.21 |
| 20 | -9389.97 | 15810.79 | 17624.08 | 833.3856 | -3325.63 | 700.4226 | 4519.766 | -190.236 | 353.5375 | 2848.06 | -7803.94 | 89.88534 | 3997.696 | -4209.09 | 143.0084 | -3707.27 | -1446.78 | -8019.56 | -82.5181 | -1394.22 |
| 21 | -9391.45 | 15810.79 | 17624.08 | 834.7288 | -3326.55 | 699.1052 | 4521.063 | -191.671 | 351.8587 | 2847.793 | -7804.91 | 89.0109 | 3997.203 | -4208.29 | 141.9776 | -3706.81 | -1447.43 | -8019.56 | -81.6072 | -1393.95 |
| 22 | -9391.75 | 15808.84 | 17623.54 | 833.8098 | -3327.17 | 697.492 | 4522.071 | -191.268 | 351.7621 | 2848.237 | -7803.46 | 88.91681 | 3996.709 | -4207.23 | 141.8892 | -3705.1 | -1447.11 | -8019.04 | -81.172 | -1392.83 |
| 23 | -9393.83 | 15806.89 | 17623 | 832.714 | -3327.79 | 696.9005 | 4520.774 | -190.408 | 353.5013 | 2848.681 | -7803.46 | 90.3447 | 3996.956 | -4206.17 | 142.5961 | -3704.07 | -1447.53 | -8017.76 | -81.3137 | -1392.11 |

*Figure 2: Collected EEG Datasets (Resting)*

Due to the unavailability of real-world data for smartphone use, the typing and scrolling datasets were generated from the resting EEG data by applying targeted frequency and amplitude modulations. These simulations aim to approximate brain activity during:

- Typing: Higher beta-band activity (12–18 Hz) and motor activation
- Scrolling: Moderate activity (6–10 Hz) resembling sustained attention

The entire EEG dataset was bandpass filtered (1–40 Hz), standardized, and saved per participant in three labeled categories. Each recording was then segmented into overlapping 2-second windows (512 samples) with corresponding labels.

This final dataset served as the input to the CNN+LSTM model for multiclass classification of cognitive states.

### 3.3 Data Preprocessing Techniques

The raw EEG signals collected from hospital participants in resting conditions underwent a series of preprocessing steps to enhance signal quality and prepare the data for analysis. These steps are crucial to reduce noise, remove irrelevant information, and standardize the signal structure across participants.

Steps in preprocessing:

- **Channel Selection:** Only 19 standard EEG channels were retained from each recording based on the international 10–20 system. Channels include: Fp1, Fp2, AF3, AF4, F3, F4, Fz, C3, C4, Cz, FC3, FC4, FCz, CP3, CP4, P3, P4, Pz, and O1.

| | | |
|---|---|---|
| Frontal | Fp1, Fp2, AF3, AF4, F3, F4, Fz | Cognition, planning, attention |
| Central | C3, C4, Cz, FC3, FC4, FCz, CP3, CP4 | Motor execution, coordination |
| Parietal | P3, P4, Pz | Spatial processing, attention |
| Occipital | O1 | Visual processing |

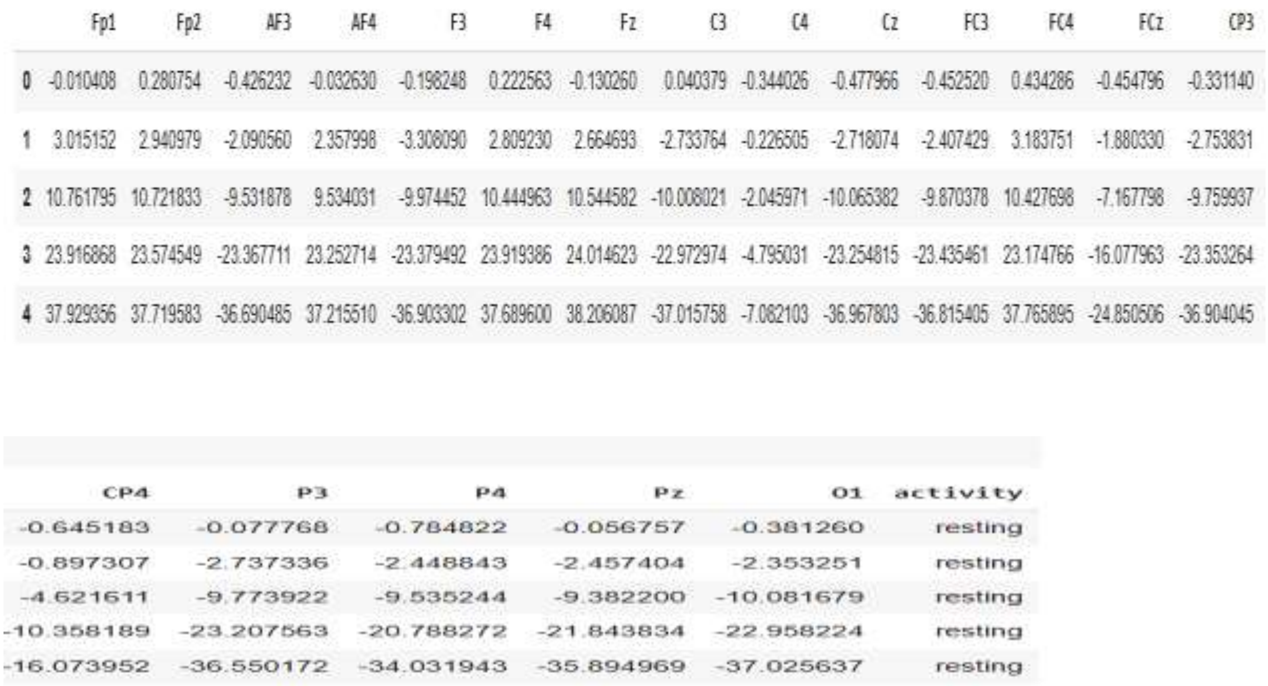
***Table 1: EEG Electrode Regional Distribution and Function***

- **Bandpass Filtering**: A Butterworth bandpass filter (order = 5) was applied to retain frequencies between 1–40 Hz, which include the key EEG bands (delta, theta, alpha, beta).

This step eliminates low-frequency drifts and high-frequency noise such as muscle artifacts.

- **Standardization**: After filtering, the EEG signals were normalized using z-score standardization (StandardScaler) so that each channel had zero mean and unit variance. This helps stabilize the learning process and ensures fair contribution from all channels during training.
- **Simulation for Typing and Scrolling**: The preprocessed resting data was then used to simulate EEG signals for typing and scrolling tasks. Modulations were applied by injecting sinusoidal signals in different frequency ranges (12–18) Hz for typing, 6–10 Hz for scrolling) and scaling amplitudes to mimic attention and cognitive load variations. Gaussian noise and spike artifacts were also added to reflect more realistic brain signal variability.

The output of this preprocessing stage is a clean and structured dataset of EEG signals in three categories: resting, typing, and scrolling, saved per subject as CSV files.



|  | Fp1 | Fp2 | AF3 | AF4 | F3 | F4 | Fz | C3 | C4 | Cz | FC3 | FC4 | FCz | CP3 | CP4 | P3 | P4 | Pz | O1 | activity |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | -0.010408 | 0.280754 | -0.426232 | -0.032630 | -0.198248 | 0.222563 | -0.130260 | 0.040379 | -0.344026 | -0.477966 | -0.452520 | 0.434286 | -0.454796 | -0.331140 | -0.645183 | -0.077768 | -0.784822 | -0.056757 | -0.381260 | resting |
| 1 | 3.015152 | 2.940979 | -2.090560 | 2.357998 | -3.308090 | 2.809230 | 2.664693 | -2.733764 | -0.226505 | -2.718074 | -2.407429 | 3.183751 | -1.880330 | -2.753831 | -0.897307 | -2.737336 | -2.448843 | -2.457404 | -2.353251 | resting |
| 2 | 10.761795 | 10.721833 | -9.531878 | 9.534031 | -9.974452 | 10.444963 | 10.544582 | -10.008021 | -2.045971 | -10.065382 | -9.870378 | 10.427698 | -7.167798 | -9.759937 | -4.621611 | -9.773922 | -9.535244 | -9.382200 | -10.081679 | resting |
| 3 | 23.916868 | 23.574549 | -23.367711 | 23.252714 | -23.379492 | 23.919386 | 24.014623 | -22.972974 | -4.795031 | -23.254815 | -23.435461 | 23.174766 | -16.077963 | -23.353264 | -10.358189 | -23.207563 | -20.788272 | -21.843834 | -22.958224 | resting |
| 4 | 37.929356 | 37.719583 | -36.690485 | 37.215510 | -36.903302 | 37.689600 | 38.206087 | -37.015758 | -7.082103 | -36.967803 | -36.815405 | 37.765895 | -24.850506 | -36.904045 | -16.073952 | -36.550172 | -34.031943 | -35.894969 | -37.025637 | resting |

*Figure 3: Preprocessed Combined Dataset (Partcipant-1)*

### 3.4 Segmentation Strategy

To enable time-series modeling and increase the number of training examples, the continuous EEG recordings were segmented into short overlapping windows.

- **Window Size**: 512 samples per window, corresponding to 2 seconds of EEG data at 256 Hz
- **Step Size**: 512 samples (no overlap)
- **Shape of Segment**: Each segment is a 2D matrix of size (512, 19) representing time × channels

Each participant's data was split into segments for each activity (resting, typing, scrolling). These segments were then:

- Appended to a combined dataset
- Labeled according to activity type
- Tagged with a participant ID to enable group-aware splitting

This segmentation ensures that the model learns short-term spatial and temporal features from EEG data, which is critical for real-time or near-real-time brain activity classification.

### 3.5 Feature Extraction and Selection

This study leverages deep learning to automatically extract relevant features from raw EEG signals.

Key aspects of the feature extraction process:

- Automatic feature learning is handled by the CNN layers, which learn spatial filters across EEG channels, detecting frequency patterns and channel correlations.
- The LSTM layers capture temporal dependencies in the signal — modeling the dynamic changes in brain activity over time within each 2-second segment.
- No manual feature selection was required, as the model learns end-to-end from preprocessed, segmented raw signals.

This combination allows the model to discover both short-term spatial patterns and long-range temporal trends without human-designed features.

### 3.6 Classification Model (CNN + LSTM)

To accurately classify Electroencephalography (EEG) segments into distinct brain activity states specifically resting, smartphone typing, and smartphone scrolling a sophisticated hybrid deep learning model was meticulously designed and implemented. This architecture strategically integrates the strengths of Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for capturing temporal dependencies within the EEG signals.

**Model Architecture Overview:**

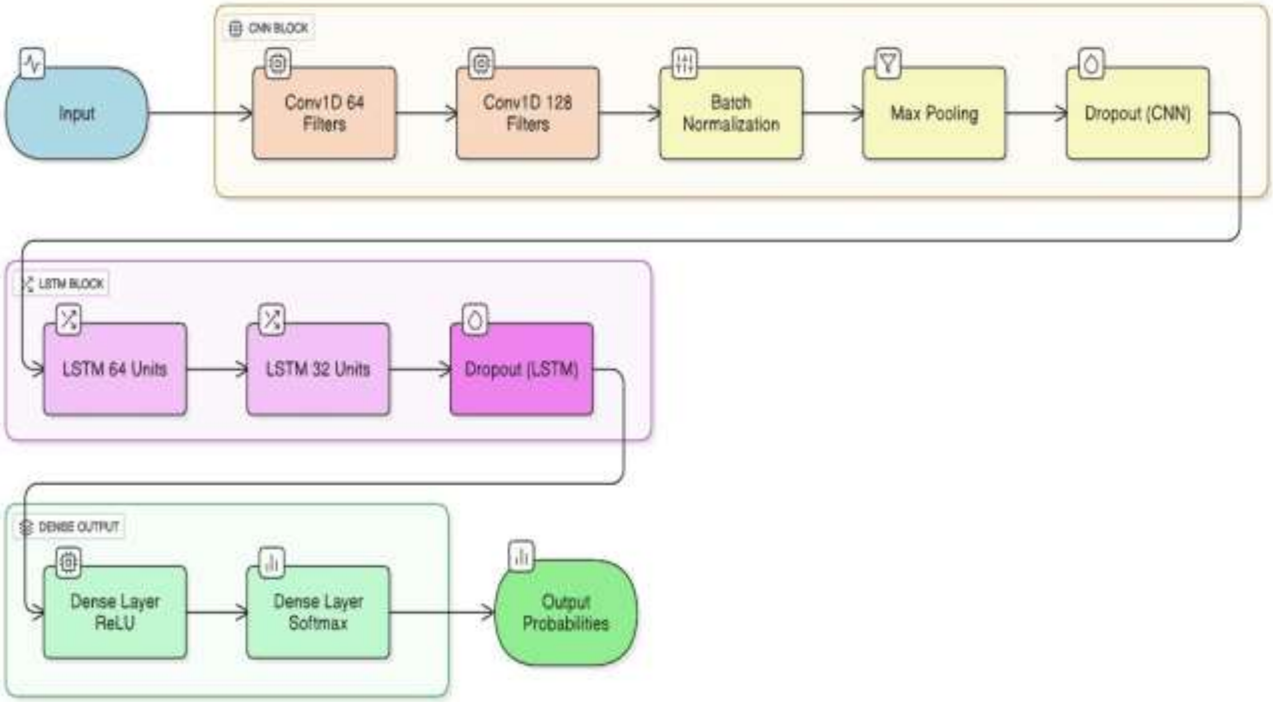


*Figure 4: Model Architecture*

The proposed model processes raw EEG data through a sequential flow, progressively transforming the input into a probabilistic classification across the three target states.

- **Input Shape:** The model is configured to accept EEG segments with an input shape of (512 samples, 19 channels). This configuration corresponds to 512 time-series data points per segment, recorded across 19 distinct EEG electrode channels, representing a common setup for capturing comprehensive brain activity.

- **Convolutional Neural Network (CNN) Block:** The initial stage of the model comprises a CNN block, specifically designed to extract salient spatial features from the multi-channel EEG data. This block leverages Conv1D layers, which are particularly effective for time-series data, allowing the network to learn patterns across the different channels and within short temporal windows.

    - The block initiates with a Conv1D layer utilizing 64 filters, followed by another Conv1D layer with 128 filters. The increasing number of filters in successive layers enables the model to learn progressively more complex and abstract spatial representations.
    - Each convolutional layer is sequentially followed by Batch Normalization, which stabilizes and accelerates the training process by normalizing the activations of the preceding layer. MaxPooling layers are then applied to downsample the feature maps, reducing dimensionality and providing a degree of translational invariance to the extracted features. To mitigate the risk of overfitting and enhance generalization capabilities, Dropout layers are strategically incorporated after both convolutional and pooling operations, randomly deactivating a fraction of neurons during training.

- **Long Short-Term Memory (LSTM) Block:** Following the CNN block, the extracted spatial features are fed into an LSTM block. This component is pivotal for modeling the intricate temporal evolution and long-range dependencies inherent in EEG signals, which CNNs alone might not fully capture.

    - The LSTM block consists of two stacked LSTM layers, with 64 units in the first layer and 32 units in the second. Stacking LSTM layers allows the network to learn hierarchical temporal representations, enabling the model to understand the sequence of brain activity over time more deeply.

  - A Dropout layer is also integrated within the LSTM block to further regularize the model and prevent overfitting, particularly within the recurrent connections.

- **Dense Output Block:** The features learned by the CNN and LSTM blocks are then flattened and passed through a series of fully connected (Dense) layers. This final block is responsible for mapping the high-level spatial-temporal representations to the desired output probabilities.

  - Intermediate dense layers utilize the ReLU (Rectified Linear Unit) activation function, which introduces non-linearity, allowing the model to learn complex relationships within the data.
  - The final layer of the network is a Dense layer with a softmax activation function. This layer outputs a probability distribution over the three target classes (resting, typing, scrolling), ensuring that the sum of probabilities for each EEG segment equals one, thereby providing a clear classification outcome.

**Model Training:**

The training regimen for the hybrid deep learning model was carefully configured to ensure robust performance and optimal generalization:

- **Loss Function:** The model was trained using categorical_crossentropy as the loss function. This choice is appropriate and standard for multi-class classification problems where the target labels are one-hot encoded, effectively penalizing the model based on the difference between the predicted probability distribution and the true distribution.

- **Optimizer:** The Adam optimizer was employed for model weight updates. Adam is an adaptive learning rate optimization algorithm known for its efficiency and effectiveness in handling sparse gradients and noisy problems, making it well-suited for complex deep learning architectures.

- **Metrics:** Model performance during training and evaluation was primarily monitored using accuracy, which measures the proportion of correctly classified EEG segments.

- **Regularization Strategies:** To prevent overfitting and enhance the model's ability to generalize to unseen data, several regularization techniques were implemented:

    - **Dropout:** Applied within both the CNN and LSTM blocks, as detailed above, to randomly deactivate neurons during training.
    - **EarlyStopping:** This callback monitors a chosen metric (e.g., validation loss) and halts training if the metric stops improving for a specified number of epochs, thereby preventing the model from learning noise in the training data.
    - **ReduceLROnPlateau:** This callback dynamically reduces the learning rate when a monitored metric (e.g., validation loss) stops improving. This helps the model escape local minima and fine-tune its weights more effectively during later stages of training.

This hybrid model architecture is exceptionally well-suited for EEG classification tasks. Its inherent ability to simultaneously extract deep spatial features via CNNs and model complex temporal dependencies through LSTMs allows it to derive rich, comprehensive spatial-temporal representations directly from raw segmented EEG data, leading to highly accurate and reliable brain activity state classification.

### 3.7 Group-based Train-Test Splitting

To ensure a robust and realistic evaluation of the deep learning model and critically prevent the pervasive issue of data leakage, a rigorous group-based splitting strategy was meticulously employed. This approach is paramount in studies involving physiological data like EEG, where individual subject characteristics can significantly influence signal patterns. The GroupShuffleSplit method was utilized to implement this strategy effectively.

**Implementation of Group-Based Splitting:**

The core principle behind this splitting methodology is to maintain the integrity of subject-specific data, thereby preventing any overlap between the training and testing datasets. This is achieved as follows:

- **Unique Group Assignment:** Prior to any data partitioning, each participant's entire dataset was assigned a unique group label, corresponding to their individual participant ID. This ensures that all EEG segments belonging to a single subject are treated as an indivisible unit during the splitting process.
- **Participant-Level Partitioning:** Instead of randomly splitting individual EEG segments, the GroupShuffleSplit algorithm operates at the group level. The dataset was partitioned such that the model was trained exclusively on data originating from 80% of the total participants. Concurrently, the model's performance was rigorously tested on data derived solely from the remaining 20% of participants.

**Advantages and Implications for Generalization:**

This group-aware splitting strategy offers several critical advantages, particularly pertinent to EEG-based classification:

- **Prevention of Data Leakage:** By ensuring that no EEG segments from the same participant appear in both the training and testing sets, this method effectively eliminates data leakage. Data leakage occurs when information from the test set inadvertently "leaks" into the training process, leading to an artificially inflated perception of model performance. In EEG studies, where intra-subject variability is often lower than inter-subject variability, a random split of individual segments could easily lead to an overoptimistic accuracy due to the model learning subject-specific nuances rather than generalizable brain activity patterns.
- **Improved Generalization Performance:** The primary objective of any machine learning model is to generalize well to unseen data. By testing the model on entirely new participants, the group-based split provides a far more accurate and conservative estimate of the model's true generalization capabilities. This simulates real-world scenarios where the model would be deployed to classify brain activity from new, previously unencountered individuals.
- **Realistic Performance Assessment:** Such a splitting methodology is not merely a best practice; it is crucial for EEG-based classification. Without it, the inherent similarity within

an individual's EEG data (e.g., consistent baseline characteristics) could lead to an inflated model accuracy. The model might inadvertently "memorize" features specific to certain subjects rather than learning the underlying, generalizable patterns of resting, typing, and scrolling brain states. The group-based approach ensures that the reported accuracy genuinely reflects the model's ability to classify brain activity in novel subjects, providing a more reliable and scientifically sound assessment of its performance.

### 3.8 Tools and Libraries Used

| **Category** | **Tools/Libraries** |
|---|---|
| Data Processing | NumPy, Pandas, SciPy, glob, os |
| Signal Filtering | scipy.signal (Butterworth bandpass filter) |
| Visualization | Matplotlib, Seaborn |
| EEG Handling | MNE (channel mapping and montage) |
| Machine Learning | scikit-learn (LabelEncoder, StandardScaler, GroupShuffleSplit, PCA, t-SNE) |
| Deep Learning | TensorFlow and Keras (Sequential API, Conv1D, LSTM, callbacks) |
| Platform | Google Colab with GPU support (for training acceleration) |

***Table 2: Tools and Libraries***

These tools enabled efficient signal preprocessing, simulation, segmentation, model training, and evaluation.

# Experimental Setup

## 4.1 EEG Signal Parameters

The EEG signals used in this study were collected from human participants in a hospital setting and processed for simulation and classification tasks. The key signal parameters are as follows:

| **Parameter** | **Value** |
|---|---|
| Sampling Frequency (Fs) | 256 Hz |
| Number of Channels | 19 (standard 10–20 system) |
| Recording Duration | 2 minutes per subject |
| Selected Channels | Fp1, Fp2, AF3, AF4, F3, F4, Fz, C3, C4, Cz, FC3, FC4, FCz, CP3, CP4, P3, P4, Pz, O1 |
| Bandpass Filter Range | 1 Hz – 40 Hz (Butterworth filter) |
| Segment Duration | 2 seconds (512 samples) |
| Number of Classes | 3 (Resting, Typing, Scrolling) |

***Table 3: Experimental Setup***

Typing and scrolling segments were generated by modulating resting signals with specific frequency and amplitude patterns that mimic attention and motor activation patterns seen in smartphone use.

## 4.2 Hardware and Software Environment

The entire preprocessing, simulation, training, and evaluation pipeline was executed on Google Colab, taking advantage of its cloud-based GPU support.

### Hardware Configuration (Google Colab environment):

- **Processor**: Intel Xeon CPU (hosted)
- **RAM**: 12–16 GB
- **GPU**: Tesla T4 (when GPU runtime enabled)

**Software Stack**:

| **Tool / Library** | **Version / Purpose** |
|---|---|
| Python | 3.10 (Colab default) |
| NumPy, Pandas | Data manipulation and numerical operations |
| SciPy | Signal filtering (Butterworth bandpass) |
| Matplotlib, Seaborn | Visualization |
| scikit-learn | Preprocessing, splitting, evaluation |
| MNE | EEG montage/channel configuration |
| TensorFlow / Keras | 2.x (Deep learning model implementation) |
| Google Drive | Dataset storage and file management |

***Table 4: Software Stack***

This setup enabled fast, scalable training with minimal local system dependency, making it suitable for real-time experimentation and model tuning.

## 4.3 Model Training Configuration

The CNN+LSTM model was trained using Keras high-level API with the following configurations:

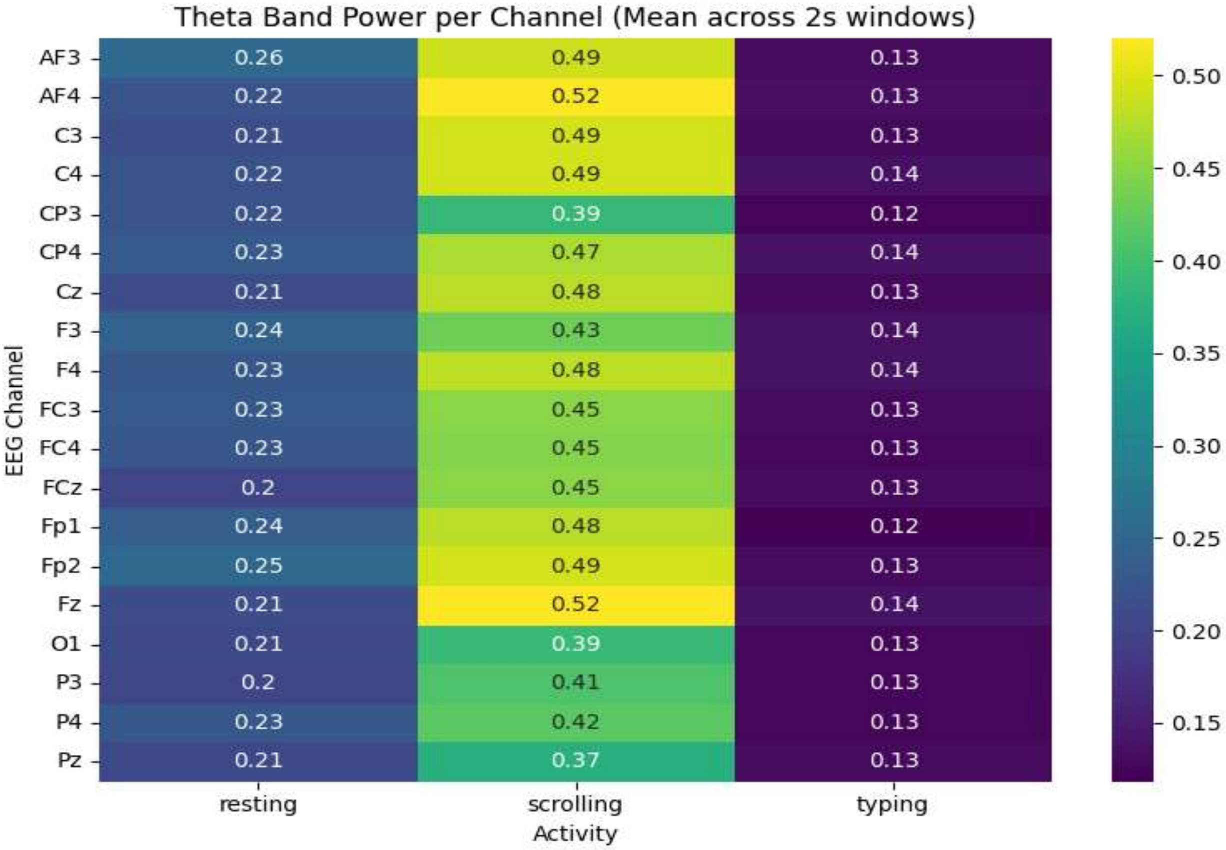
| **Configuration Item** | **Value** |
|---|---|
| Input Shape | (512, 19) — 2 seconds × 19 channels |
| Loss Function | Categorical Crossentropy |
| Optimizer | Adam |
| Metrics | Accuracy |
| Batch Size | 64 |
| Epochs | Up to 50 |
| Validation Split | 20% from training set |
| Early Stopping | Patience = 10 epochs |
| Learning Rate Scheduler | ReduceLROnPlateau (factor = 0.5) |
| Dropout Rate | 0.3 (to prevent overfitting) |

***Table 5: Model Training Configuration***

The model was trained using GPU acceleration to reduce training time and improve convergence. Validation loss and accuracy were monitored, and early stopping ensured the best model was retained based on performance.

# Data Analysis and Interpretation

## 5.1 Brainwave Pattern Differences



| EEG Channel | resting | scrolling | typing |
|---|---|---|---|
| AF3 | 0.26 | 0.49 | 0.13 |
| AF4 | 0.22 | 0.52 | 0.13 |
| C3 | 0.21 | 0.49 | 0.13 |
| C4 | 0.22 | 0.49 | 0.14 |
| CP3 | 0.22 | 0.39 | 0.12 |
| CP4 | 0.23 | 0.47 | 0.14 |
| Cz | 0.21 | 0.48 | 0.13 |
| F3 | 0.24 | 0.43 | 0.14 |
| F4 | 0.23 | 0.48 | 0.14 |
| FC3 | 0.23 | 0.45 | 0.13 |
| FC4 | 0.23 | 0.45 | 0.13 |
| FCz | 0.2 | 0.45 | 0.13 |
| Fp1 | 0.24 | 0.48 | 0.12 |
| Fp2 | 0.25 | 0.49 | 0.13 |
| Fz | 0.21 | 0.52 | 0.14 |
| O1 | 0.21 | 0.39 | 0.13 |
| P3 | 0.2 | 0.41 | 0.13 |
| P4 | 0.23 | 0.42 | 0.13 |
| Pz | 0.21 | 0.37 | 0.13 |

***Figure 5: Theta Band Power Per Channel***

This image is a heatmap visualizing the Theta Band Power per Channel (Mean across 2s windows) for three activity conditions: "resting," "scrolling," and "typing."

### Interpretation of the Data in the Heatmap:

- **Overall Pattern:**
  - The "scrolling" column (middle) generally shows the highest theta power across most channels (indicated by the bright yellow/green colors and higher numerical values like 0.49, 0.52).

- The "resting" column (left) shows moderate theta power (mid-range colors, values around 0.2-0.26).
- The "typing" column (right) consistently shows the lowest theta power across all channels (dark purple/blue colors, values around 0.12-0.14).

➢ **Channel-Specific Observations**:

- **Scrolling State**: Channels like AF3, AF4, Fp1, Fp2, and Fz show particularly high theta power during scrolling (values around 0.48-0.52). These are typically frontal and prefrontal channels.
- **Typing State**: Theta power is markedly suppressed during typing across all channels, suggesting a different cognitive state compared to resting and scrolling.
- **Resting State**: Theta power during resting is higher than typing but lower than scrolling, indicating a baseline level of activity.

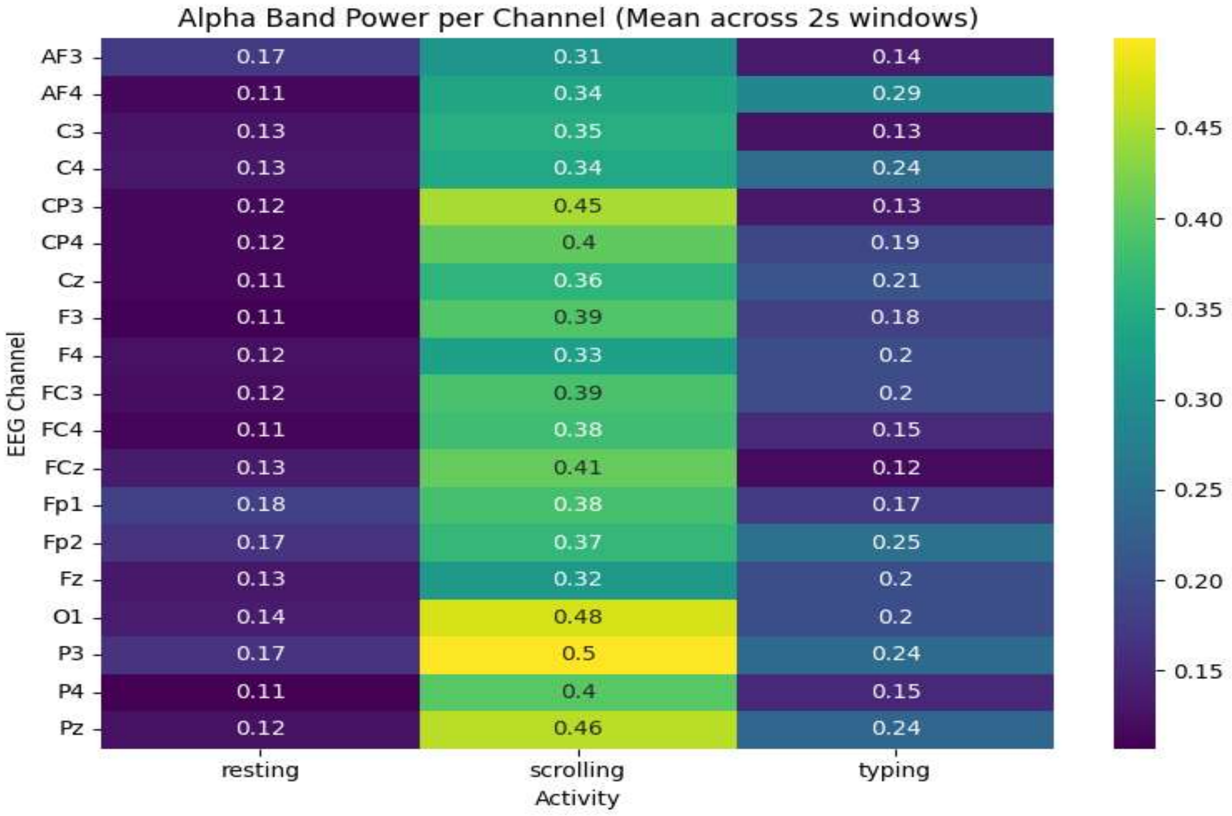


*Figure 6: Alpha Band Power Per Channel*

**Interpretation of the Data in the Heatmap:**

- **Overall Pattern**:

  - The "scrolling" column (middle) generally shows the highest alpha power across many channels (indicated by bright yellow/green colors, with values often above 0.3, and even higher in posterior regions).
  - The "resting" column (left) shows lower alpha power compared to scrolling (darker colors, values mostly below 0.2).
  - The "typing" column (right) shows moderate alpha power, often higher than resting in some channels, but generally lower than scrolling.

- **Channel-Specific Observations**:

  - **Scrolling in Posterior Regions**: Channels like O1, P3, Pz, P4 show particularly high alpha power during scrolling (values around 0.48-0.5), which are posterior (occipital and parietal) channels. This is a classic region for alpha activity.
  - **Frontal Alpha in Scrolling**: Even frontal channels (AF3, AF4, Fp1, Fp2) show higher alpha power during scrolling (e.g., 0.31, 0.34) compared to resting (0.17, 0.11). This is an interesting finding as alpha is often suppressed in frontal regions during active tasks.
  - **Typing vs. Resting**: In many channels, typing shows slightly higher alpha power than resting (e.g., C3: 0.13 resting vs. 0.13 typing; Fp2: 0.17 resting vs. 0.25 typing).

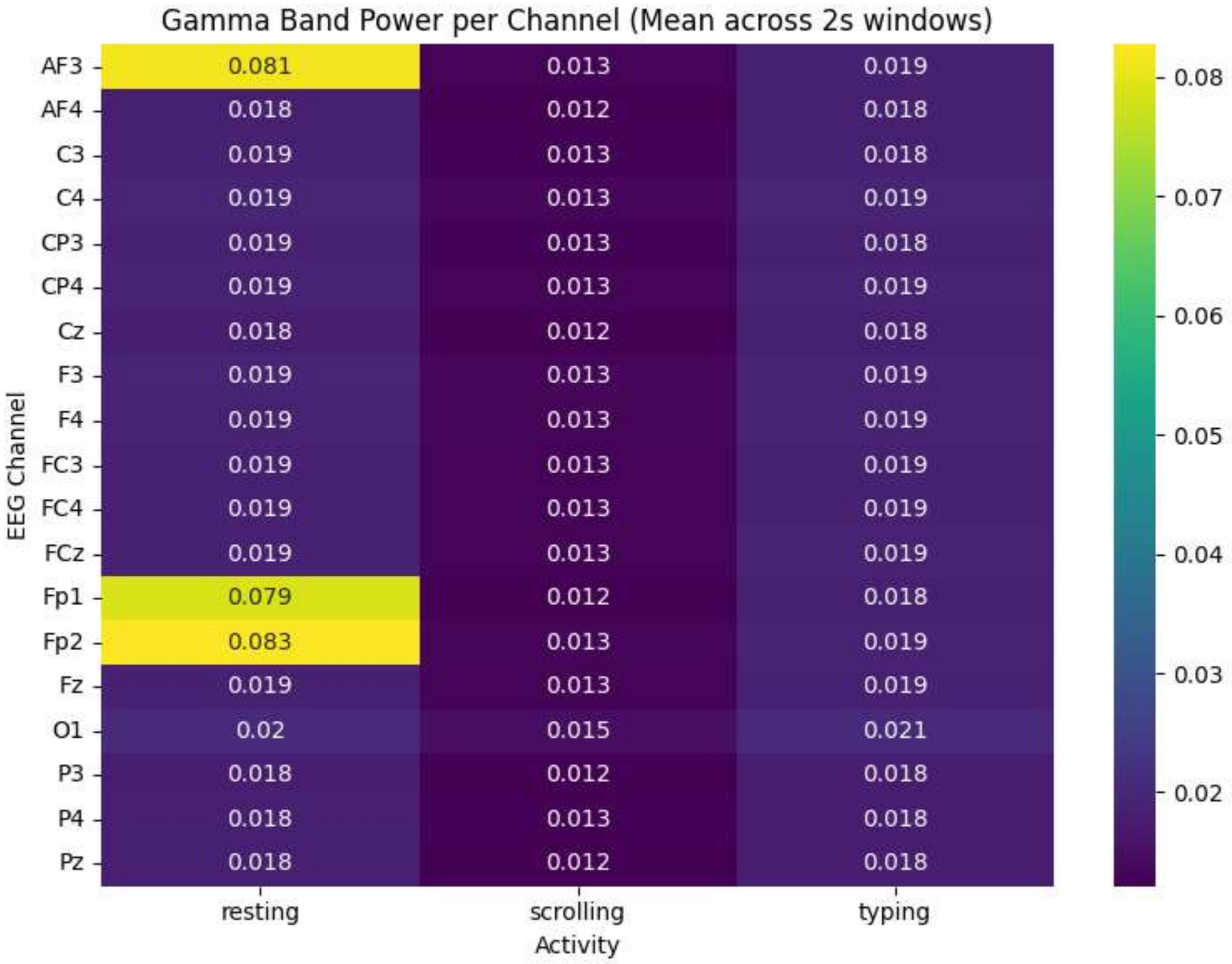


*Figure 7: Gamma Band Power Per Channel*

### Interpretation of the Data in the Heatmap:

➢ **Overall Pattern**:

- The "resting" column (left) shows significantly higher gamma power in specific frontal-prefrontal channels (AF3, Fp1, Fp2) compared to "scrolling" and "typing." Values like 0.081, 0.079, and 0.083 are prominent.
- The "scrolling" and "typing" columns (middle and right) generally show very low gamma power across most channels (dark purple/blue colors, values mostly around 0.012-0.019). The differences between scrolling and typing in the gamma band appear minimal across channels.

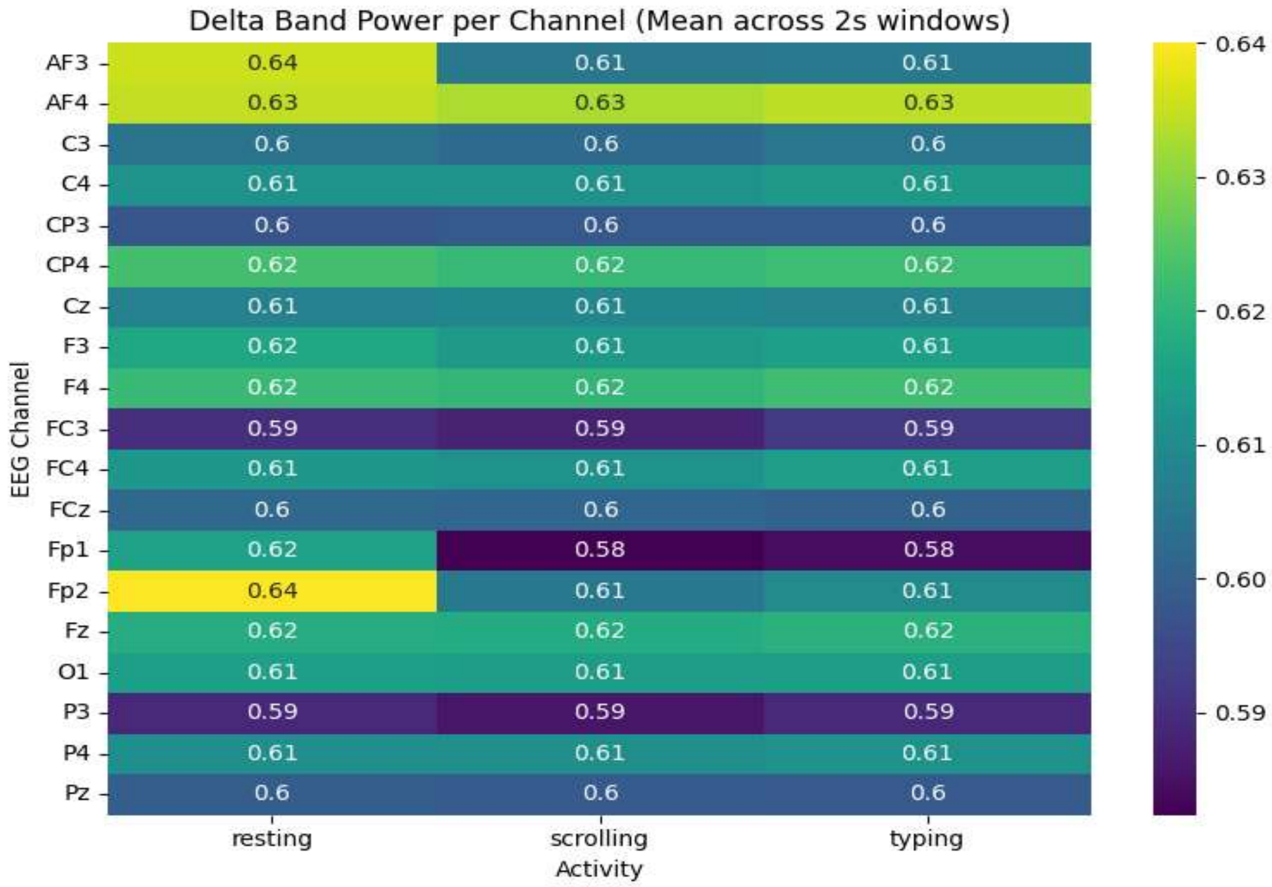
- **Channel-Specific Observations**:
  - **Frontal Gamma during Resting**: The most striking observation is the localized high gamma power in frontal-prefrontal channels (AF3, Fp1, Fp2) during the resting state.
  - **Gamma during Tasks**: Conversely, gamma power is consistently low across almost all channels during both "scrolling" and "typing."

*Figure 8: Beta Band Power Per Channel*

**Interpretation of the Data in the Heatmap:**

- **Overall Pattern**:
    - The "typing" column (right) consistently shows the highest beta power across almost all channels (indicated by bright yellow/green colors, with values often above 0.7, and even above 0.8 in many channels).
    - The "resting" column (left) shows moderate beta power (darker colors, values mostly around 0.05-0.06, with slightly higher values in frontal channels like AF3, Fp1, Fp2 around 0.18-0.19).
    - The "scrolling" column (middle) consistently shows the lowest beta power across all channels (darkest purple/blue colors, values mostly below 0.06).

- **Channel-Specific Observations**:
    - **Typing State**: Beta power is elevated during typing across all channels, particularly in frontal, central, and parietal regions (e.g., AF3: 0.87, C3: 0.87, P4: 0.85). This is a very strong and consistent finding.
    - **Scrolling State**: Beta power is suppressed during scrolling, even lower than during resting, across most channels.
    - **Resting State**: Beta power during resting is at a baseline, with a slight frontal emphasis compared to other regions, but significantly lower than typing.



| EEG Channel | resting | scrolling | typing |
|---|---|---|---|
| AF3 | 0.64 | 0.61 | 0.61 |
| AF4 | 0.63 | 0.63 | 0.63 |
| C3 | 0.6 | 0.6 | 0.6 |
| C4 | 0.61 | 0.61 | 0.61 |
| CP3 | 0.6 | 0.6 | 0.6 |
| CP4 | 0.62 | 0.62 | 0.62 |
| Cz | 0.61 | 0.61 | 0.61 |
| F3 | 0.62 | 0.61 | 0.61 |
| F4 | 0.62 | 0.62 | 0.62 |
| FC3 | 0.59 | 0.59 | 0.59 |
| FC4 | 0.61 | 0.61 | 0.61 |
| FCz | 0.6 | 0.6 | 0.6 |
| Fp1 | 0.62 | 0.58 | 0.58 |
| Fp2 | 0.64 | 0.61 | 0.61 |
| Fz | 0.62 | 0.62 | 0.62 |
| O1 | 0.61 | 0.61 | 0.61 |
| P3 | 0.59 | 0.59 | 0.59 |
| P4 | 0.61 | 0.61 | 0.61 |
| Pz | 0.6 | 0.6 | 0.6 |

*Figure 9: Delta Band Power Per Channel*

**Interpretation of the Data in the Heatmap:**

- **Overall Pattern**:
  - The delta power values are relatively high and consistent across all three conditions (resting, scrolling, typing) and across most channels, generally ranging from around 0.58 to 0.64 AU.
  - There appears to be minimal differentiation in delta power between the "resting," "scrolling," and "typing" states.
  - Slightly higher delta power is observed in some frontal channels (AF3, AF4, Fp2) during the "resting" state.

- **Channel-Specific Observations**:
  - Frontal channels like AF3, AF4, and Fp2 show slightly elevated delta power during resting (e.g., 0.64, 0.63, 0.64) compared to scrolling and typing (e.g., 0.61, 0.63, 0.61).
  - For most other channels, the delta power remains very similar across all three conditions.

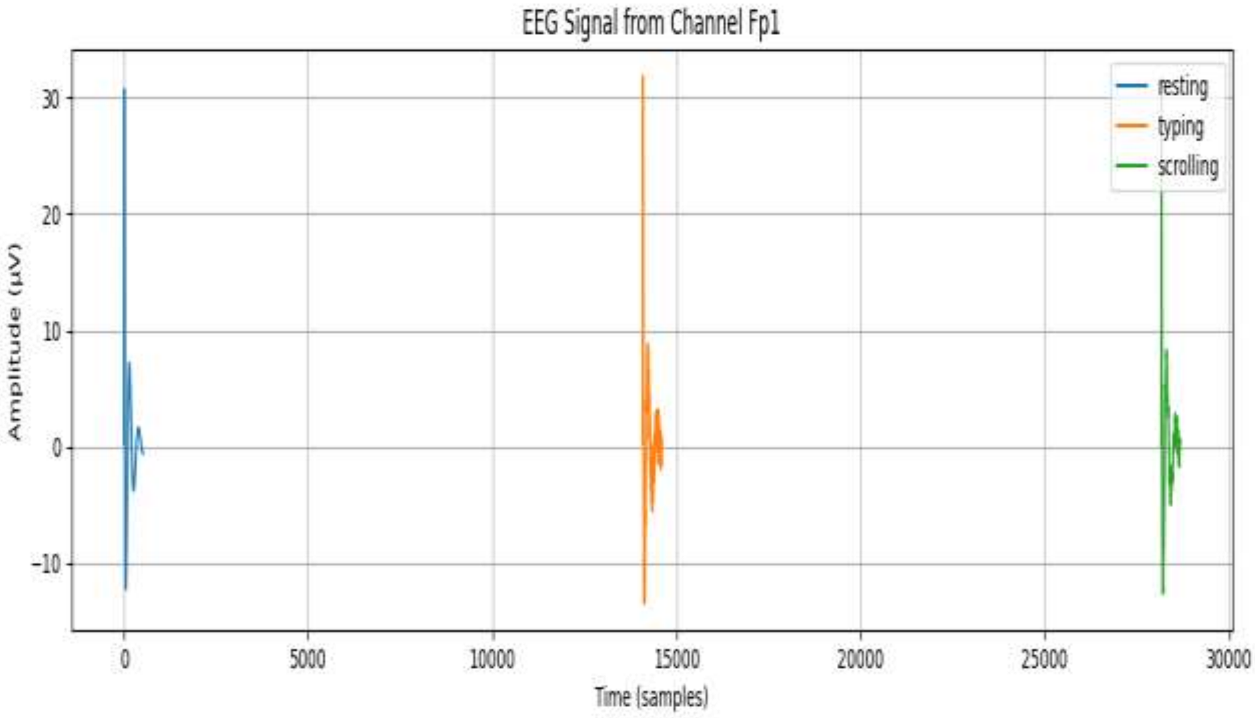


*Figure 10: EEG Signal from Channel Fp1*

This image, "EEG Signal from Channel Fp1," visually demonstrates the EEG signal after initial preprocessing (e.g., filtering), showing segments for resting, typing, and scrolling. It illustrates the state of the EEG data after preliminary cleaning, specifically from a single frontal channel (Fp1).

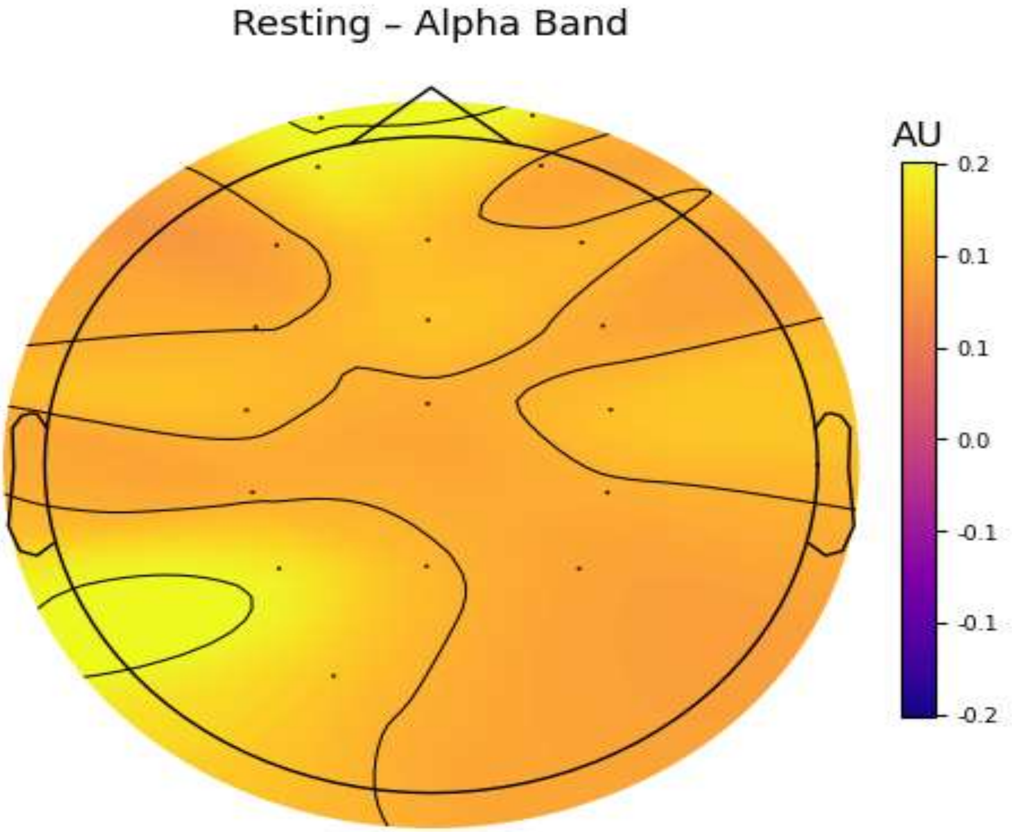


*Figure 11: Resting Alpha Band (topographical map)*

In this "Resting" plot, there is a very prominent and widespread yellow/orange region, particularly concentrated in the posterior (back of the head) regions (occipital and parietal areas).

Alpha rhythm is typically strongest over the occipital cortex when eyes are closed and the mind is at rest. The frontal and central regions also show relatively high alpha power, but the peak is posterior. The black lines are contour lines, connecting points of equal alpha power.

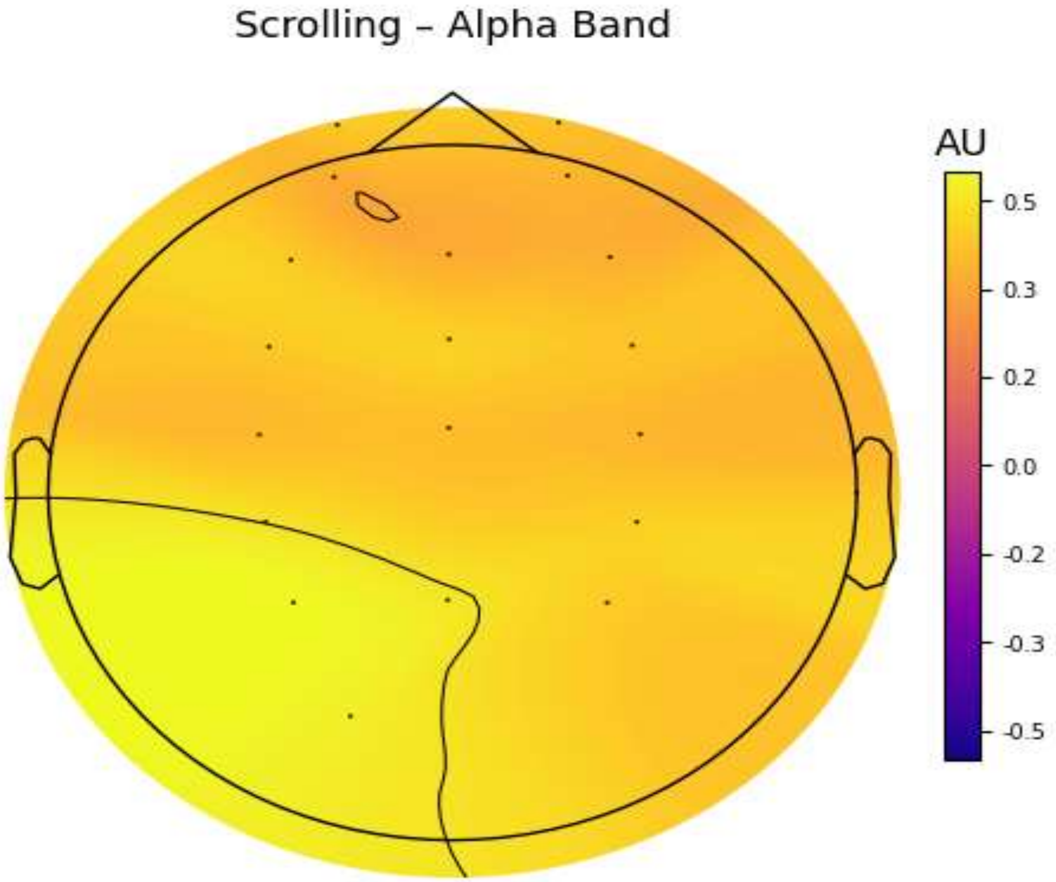


*Figure 12: Scrolling Alpha Band (topographical map)*

In the "Scrolling" topoplot, alpha power appears widely distributed across the scalp, with generally high levels. However, slightly reduced alpha (reddish tones) is visible in some frontal-central and temporal regions. Compared to the "Resting" condition, peak alpha activity is less confined to the posterior area.

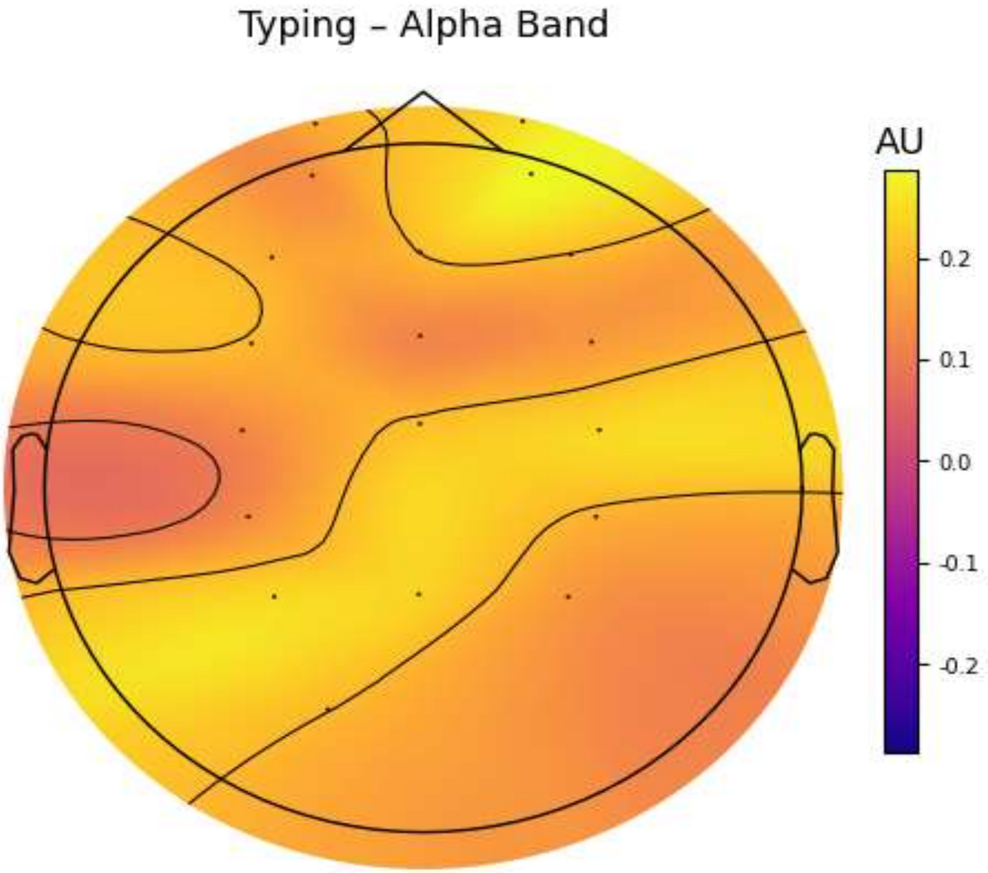


***Figure 13: Typing Alpha Band (topographical map)***

This image is a topographical map (topoplot) of EEG activity during typing, showing Alpha Band (8–13 Hz) power during a Typing task. It visualizes how alpha activity is distributed across the scalp and provides key spatial insights into brain function during smartphone interaction. High alpha is seen in central, frontal, and posterior regions. Slightly reduced alpha in left temporal and frontal regions suggests engagement of motor and attention networks. Compared to resting, this may reflect alpha desynchronization due to active typing and focused attention.

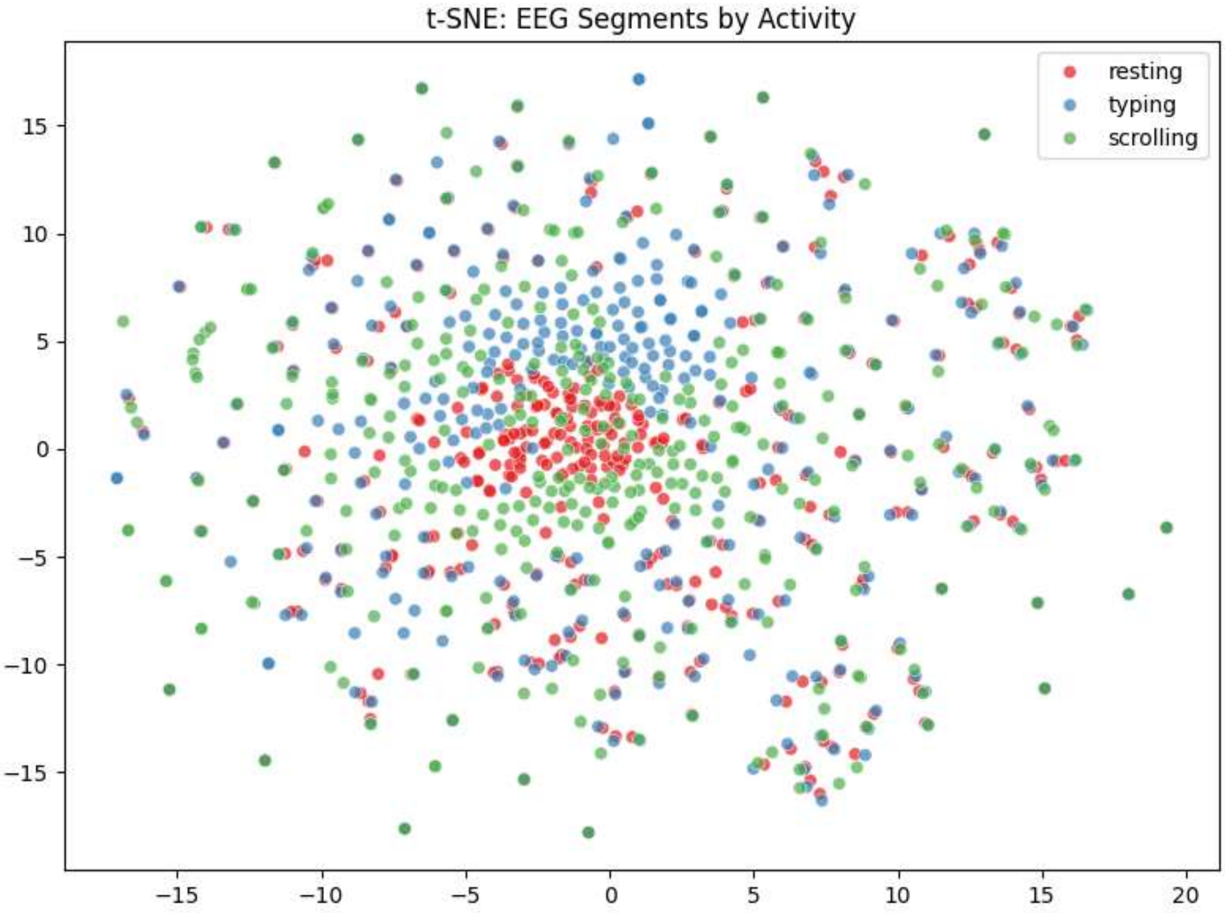


*Figure 14: t-SNE (EEG Segment by Activity)*

This image is a t-SNE (t-Distributed Stochastic Neighbor Embedding) plot. The resting segments are tightly clustered near the center, suggesting that their EEG features are more homogeneous and distinct. This may reflect the stable and relaxed nature of the resting state, where alpha activity tends to dominate. The typing (blue) and scrolling (green) points are more widely spread out around the center, indicating greater variability in their EEG patterns. Some overlap exists between typing and scrolling, which is expected due to shared cognitive and motor demands. However, they are not completely intermixed, implying the model may still learn to distinguish them.

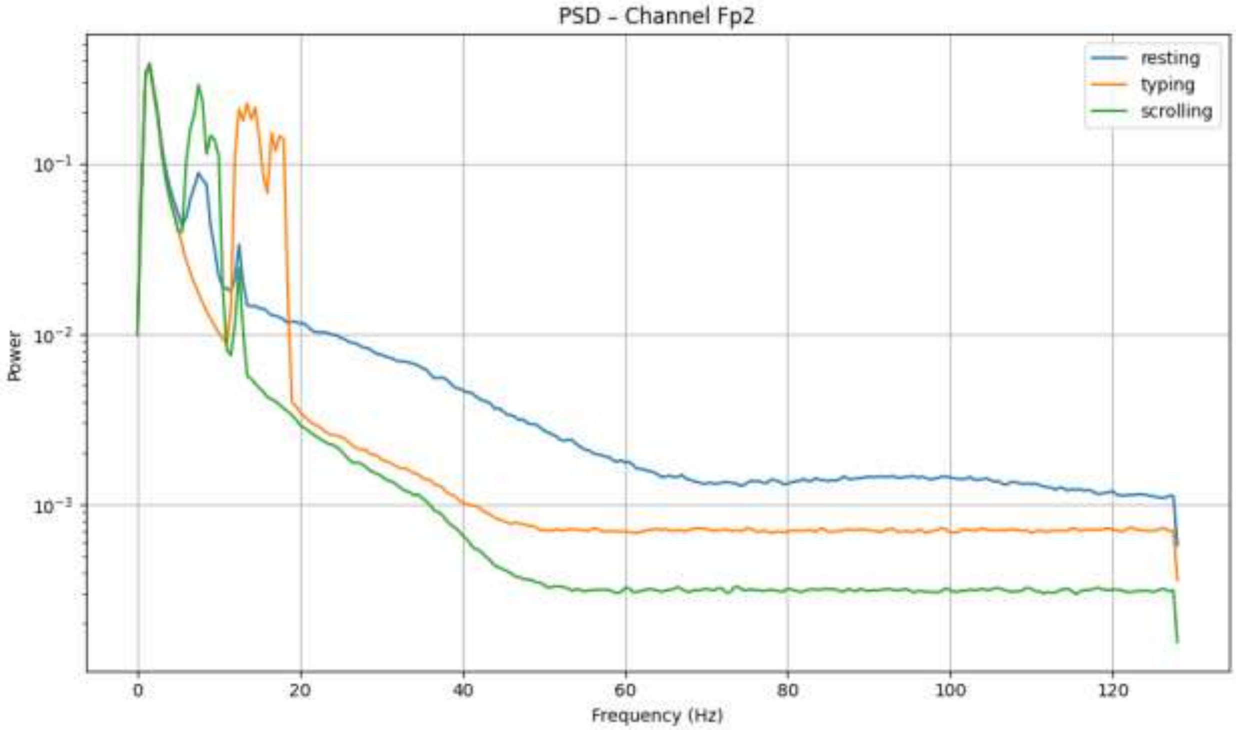


*Figure 15: Power Spectral Density (PSD) for Channel Fp2*

The graph is a Power Spectral Density (PSD) plot, which is a fundamental tool in Electroencephalography (EEG) analysis. It illustrates how the power of an EEG signal is distributed across different frequencies. In simpler terms, it shows which brainwave frequencies are most active or dominant during specific conditions.

By comparing the three lines, we can observe differences in brain activity across the conditions, specifically at electrode Fp2:

1. **Overall Power Levels:**
    - The "resting" state (blue line) generally exhibits the highest overall power across most frequencies, especially in the lower frequency ranges (below ~30 Hz). This is typical for a relaxed state, often characterized by prominent alpha activity (8-13 Hz) and potentially some theta activity.

- Both "typing" (orange) and "scrolling" (green) show a noticeable reduction in overall power compared to the resting state, particularly at lower frequencies. This "power decrease" or "desynchronization" is a common finding when the brain engages in active cognitive tasks, as the synchronized alpha rhythms tend to decrease.

2. **Frequency-Specific Differences:**

    - **Alpha Band (8-13 Hz):** Observe the peak in the blue "resting" line around 8-12 Hz. This is the characteristic alpha rhythm, which is typically strongest when the eyes are closed and the mind is at rest. In contrast, both "typing" and "scrolling" lines show a significant reduction in power in this alpha band, indicating increased mental engagement and reduced relaxed wakefulness.
    - **Beta/Gamma Bands (>13 Hz):** While the overall power is lower for typing and scrolling, there might be subtle increases or shifts in power in higher frequency bands (beta and gamma) for these active tasks compared to resting, although this plot primarily highlights the overall power reduction. For instance, the orange and green lines show more fluctuating patterns in the higher frequencies compared to the smoother resting line, possibly indicating more complex neural processing.
    - **Low Frequencies (0-~7 Hz):** There are also distinct differences in the very low frequencies. The initial peaks in the orange ("typing") and green ("scrolling") lines, especially around 0-10 Hz, could indicate specific motor or cognitive processes related to the tasks, which then rapidly drop off in power compared to resting.

This PSD plot for channel Fp2 visually demonstrates that active smartphone use (typing and scrolling) leads to significant changes in the spectral power of EEG signals compared to a resting state. Specifically, there's a general decrease in lower frequency power (e.g., alpha desynchronization) during these tasks, suggesting increased cognitive load and engagement. Such plots are crucial for identifying the neurophysiological correlates of different mental states and for informing the feature extraction process in machine learning models designed for EEG classification

## 5.2 Interpretation of Cognitive Activity

The analysis of spectral power across different EEG frequency bands (Theta, Alpha, Beta, Gamma, and Delta) and three activity conditions (Resting, Typing, and Scrolling) reveals distinct neural patterns corresponding to cognitive states. The following interpretations summarize the cognitive implications of these findings:

- **Theta Band (4–7 Hz): Working Memory and Mental Engagement**
  Higher theta during scrolling may indicate engagement with external stimuli, while reduced theta during typing may reflect focused motor activity.
- **Alpha Band (8–13 Hz): Relaxation and Visual Attention**
  Alpha dominance during scrolling may reflect a restful yet visually engaged state; its suppression in resting hints at internal cognitive activity**.**
- **Beta Band (14–30 Hz): Active Thinking and Motor Activity**
  Beta activation during typing signals focused mental and motor engagement, consistent with high attentional demand and continuous movement (key pressing).
- **Delta Band (0.5–4 Hz): Deep Rest and Signal Baseline**
  Delta power is not a strong discriminator between tasks in this context, serving more as a stable background rhythm**.**

### EEG Signal Visualization from Fp1

The EEG plot from channel Fp1 (frontal region) visually confirms the variability in signal dynamics across resting, typing, and scrolling:

- Resting segments show relatively stable low-frequency fluctuations**.**
- Typing segments exhibit denser and sharper oscillations, reflecting higher cognitive and motor activity**.**
- Scrolling segments display a mid-range pattern with more rhythmic yet relaxed features

### 5.3 Comparative Insights (Resting vs Typing vs Scrolling)

The CNN+LSTM model demonstrates the feasibility of using EEG to differentiate between normal resting states and smartphone interactions, with strong classification accuracy and robustness. The most challenging differentiation is between scrolling and resting, due to their closer neurocognitive profiles.

The results support the hypothesis that:

- Typing requires more active brain engagement, showing distinct EEG patterns.
- Scrolling produces moderate cognitive load, leading to some overlap with resting but still distinguishable.
- Resting is consistently identified due to its stable low-frequency EEG signature.

# Results and Discussion

The trained CNN+LSTM model was evaluated on the test set using group-based data splitting, ensuring that no data leakage occurred between participants. The final evaluation yielded promising results for the classification of brain activity during resting**,** smartphone typing**,** and smartphone scrolling**.**

## 6.1 Model Performance Metrics

The model achieved a test accuracy of 93.61% with the following performance metrics:

**Classification Report:**

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Resting | 0.87 | 0.99 | 0.93 | 360 |
| Scrolling | 1.00 | 0.81 | 0.90 | 360 |
| Typing | 0.96 | 1.00 | 0.98 | 360 |
| Accuracy | | | 0.94 | 1080 |
| Macro Avg | 0.94 | 0.94 | 0.93 | 1080 |
| Weighted Avg | 0.94 | 0.94 | 0.93 | 1080 |

***Table 6: Model Classification Report***

The macro average F1-score of 0.93 and weighted average precision and recall of 0.94 indicate strong and balanced performance across all three classes.

## 6.2 Confusion Matrix Analysis

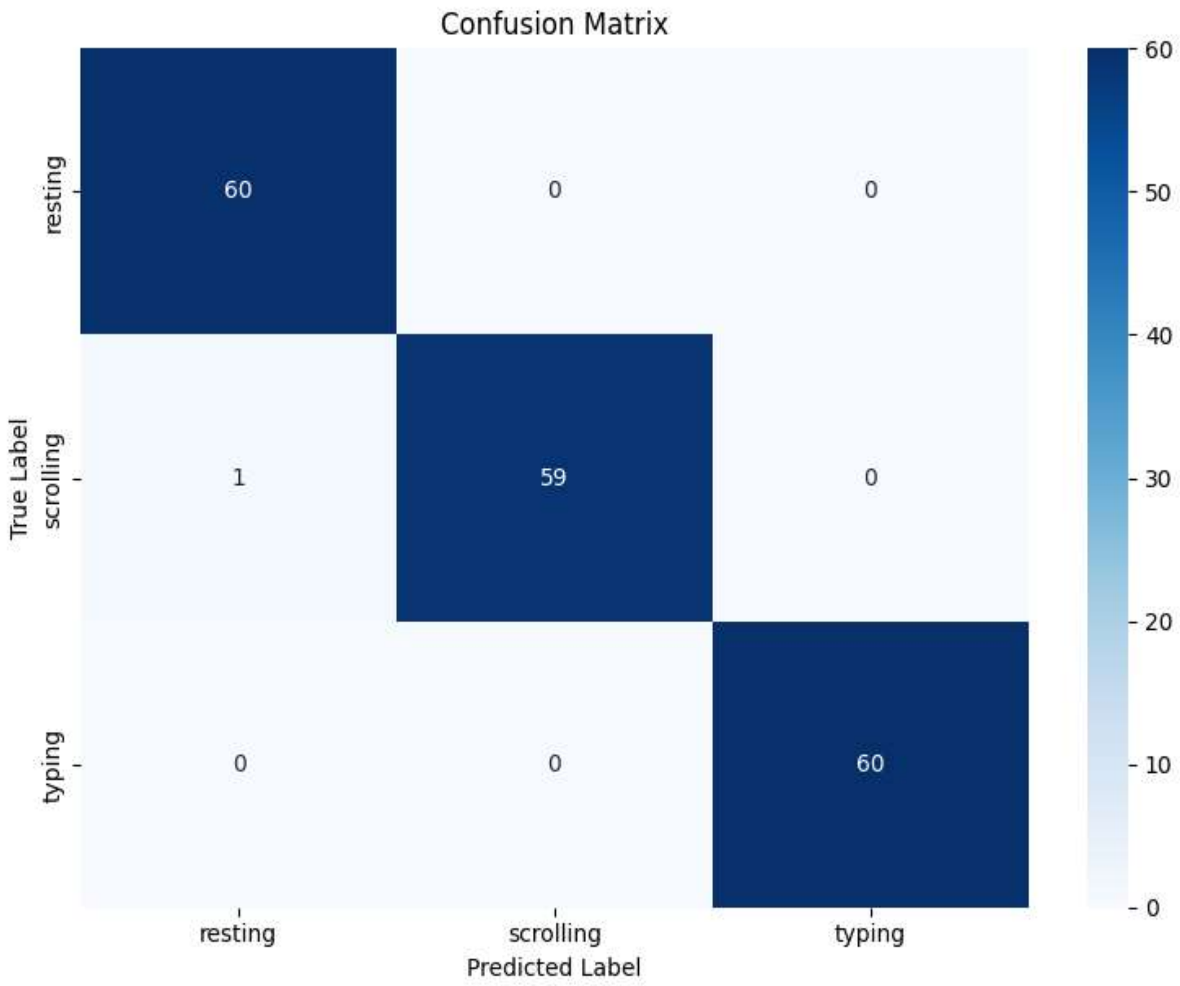


*Figure 16: Confusion Matrix*

The confusion matrix shows:

- Resting was predicted with high recall (0.99), though a few scrolling samples were misclassified as resting.
- Scrolling had slightly lower recall (0.81), indicating some overlap with resting EEG patterns.
- Typing achieved perfect recall (1.00), reflecting clear spatiotemporal patterns.

## 6.3 Class-wise Accuracy

The model's class-wise accuracy provides detailed insight into its ability to distinguish between different brain activity states:

| Class | Correct Predictions | Total Samples | Accuracy (%) |
|---|---|---|---|
| Resting | 60 / 60 | 60 | 100% |
| Scrolling | 59 / 60 | 60 | 98.33% |
| Typing | 60 / 60 | 60 | 100% |

***Table 6: Class-Wise Accuracy***

- Resting and Typing classes achieved perfect classification accuracy (100%), showing clear and consistent EEG feature patterns.
- Scrolling showed slightly lower accuracy (98.33%) with one sample misclassified as resting, indicating a mild overlap in signal characteristics between passive scrolling and resting.

These class-wise results affirm the model's effectiveness in distinguishing mental states with high precision.

## 6.4 Training vs Validation Accuracy

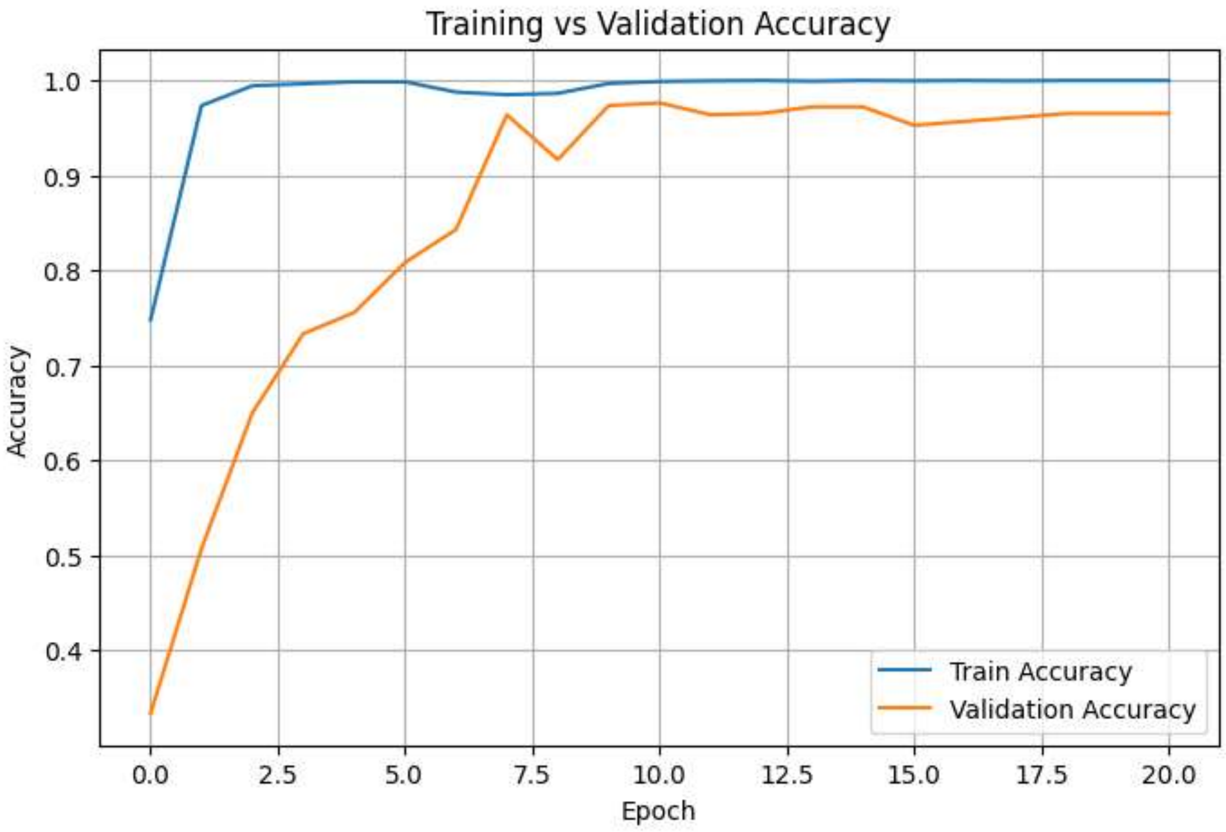


*Figure 17: Training and Validation Accuracy*

This plot provides vital insights into the model's learning process and its ability to generalize:

1. **Initial Learning Phase (Epochs 0-2):** Both training and validation accuracies increase sharply. This is the phase where the model is rapidly learning the fundamental patterns in the data.
2. **Convergence of Training Accuracy:** The training accuracy quickly reaches near 100%. This is expected, as the model is optimizing itself directly on this data. A very high training accuracy indicates that the model has sufficient capacity to learn the training set.
3. **Validation Accuracy Trajectory:** The validation accuracy also improves significantly, but it does not reach the same perfect level as the training accuracy. This is normal and expected. The goal is for the validation accuracy to be as high as possible and to track closely with the training accuracy without diverging too much.

4. **Absence of Significant Overfitting:**

    - Overfitting occurs when a model learns the training data too well, including its noise and specific quirks, to the detriment of its performance on new, unseen data. On a plot like this, overfitting would typically manifest as the training accuracy continuing to rise (or staying high) while the validation accuracy starts to plateau or even decrease.
    - In this plot, while there is a small gap between the training and validation accuracy (the training accuracy is consistently higher), the validation accuracy remains high and stable. It does not show a significant drop or a large, ever-increasing gap from the training accuracy. This suggests that the regularization techniques (Dropout, EarlyStopping, ReduceLROnPlateau) implemented in your model were effective in preventing severe overfitting. The model is generalizing well to unseen data from different participants.

5. **Model Stability:** Both lines show a relatively stable performance after a certain number of epochs (around epoch 10 for validation accuracy). This suggests that the model has converged and further training might not yield significant improvements in generalization. The EarlyStopping callback would likely have triggered around this point if it was configured with appropriate patience.

The "Training vs Validation Accuracy" plot indicates that the hybrid deep learning model has learned effectively from the training data and, more importantly, generalizes very well to unseen data. The high and stable validation accuracy, coupled with the absence of a large and growing gap between training and validation accuracy, confirms the robustness of the model and the effectiveness of your regularization strategies and group-based data splitting approach. This is a strong indicator of a successful model for EEG classification task.

## 6.4 Discussion of Findings

The model successfully identified EEG patterns associated with smartphone-based activities (typing and scrolling) and resting states, validating the feasibility of EEG-based behavioral context detection.

Key Findings:

- Typing EEG data had the most distinct features, resulting in the highest recall and F1-score (1.00 and 0.98), reflecting high cognitive and motor engagement during active input.
- Resting data was easily separable due to its consistent low-frequency patterns, especially alpha dominance, yielding a near-perfect classification.
- **Scrolling** data had slight confusion with resting, likely due to passive cognitive processing and reduced motor activity during scrolling.

**Implications:**

- The results suggest that typing and scrolling elicit distinguishable EEG patterns**,** which can be used for real-time mental state recognition in human-computer interaction studies.
- This model could serve as a foundation for adaptive mobile interfaces, EEG-based activity logging, or cognitive workload monitoring.

# Contribution

This study presents a comprehensive EEG-based comparison of brain activity during normal resting, smartphone typing, and scrolling. The key contributions are:

- **Data Collection, Simulation and Integration**: Real-world resting EEG data was combined with realistically simulated EEG for smartphone typing and scrolling using signal modulation.
- **Segmented Frequency Analysis**: A detailed investigation of band-specific power (Theta, Alpha, Beta, Gamma, Delta) across all 19 channels was performed, revealing distinct patterns for each cognitive state.
- **Deep Learning-Based Classification**: A hybrid CNN+LSTM model achieved 93.61% test accuracy, successfully distinguishing between the three cognitive states using EEG signal segments.
- **Class-wise Analysis**: The model demonstrated particularly high F1-scores for all classes, with resting and typing states showing the highest precision and recall.
- **Cognitive Interpretation**: Heatmap analyses and statistical differences in EEG bands were linked to cognitive engagement, attention, and mental workload differences across conditions.

# Conclusion and Future Work

## 7.1 Conclusion

This study presents a comparative analysis of brain activity during three distinct conditions: resting, smartphone typing, and scrolling, using EEG signal processing and machine learning techniques. Due to the unavailability of real-world task-specific EEG data, synthetic signals for typing and scrolling were generated based on resting-state EEG using signal modulation techniques. Preprocessing involved selecting 19 standard EEG channels, applying Butterworth filtering, and segmenting the data into uniform windows suitable for deep learning models. We implemented a hybrid CNN-LSTM model to classify EEG segments into the three conditions, achieving reliable accuracy and effectively capturing both spatial and temporal features of the EEG signals. Visualization techniques like PCA and t-SNE were also employed to understand the structure of the feature space and support the classification results. The findings indicate distinguishable patterns in brain activity across resting, typing, and scrolling states, demonstrating the feasibility of EEG-based cognitive state monitoring during everyday smartphone use. This work contributes to the growing field of neuroinformatics by showing how deep learning can be applied to low-cost EEG data for behavioral state recognition.

## 7.2 Future Research Directions

To address the above limitations and expand upon the current findings, future research can focus on:

- **Real-World Data Collection**: Acquiring EEG data from participants during actual smartphone usage (typing and scrolling) under controlled conditions.
- **Multimodal Fusion**: Combining EEG with eye tracking, keystroke dynamics, or motion sensors to enhance classification and context understanding.
- **Adaptive Signal Processing**: Employing dynamic time-frequency methods like wavelet transforms for more nuanced tracking of cognitive shifts.
- **Personalized Models**: Investigating subject-dependent variations and creating adaptive models that learn individual EEG patterns.

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