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NeuroResponse: EEG-Based Classification of Hemiplegia Recovery

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Group Members

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Content

Problem Statement

Understanding brain recovery in hemiplegia patients is a challenging task due to the complex and noisy nature of EEG signals. Hemiplegia, often caused by stroke or brain injury, results in paralysis on one side of the body and requires continuous assessment for effective rehabilitation. EEG provides a non-invasive method to monitor brain activity, but interpreting these signals is difficult due to subject-specific variability and external noise. Accurately classifying whether a patient is responding to treatment is essential to guide personalized rehabilitation plans and improve outcomes.

Introduction

This project focuses on classifying EEG responses of hemiplegia patients as either responding or non-responding by comparing their brain activity to that of healthy individuals. Using advanced signal processing techniques, meaningful features are extracted from the EEG data, which are then fed into machine learning and deep learning models to identify patterns. These patterns can help doctors assess how well a patient is recovering and make better decisions about rehabilitation and treatment strategies.

Objectives

- Investigate the neural response differences between hemiplegia patients and healthy individuals.
- Assess the effect of stroke-induced hemiplegia on motor imagery tasks using EEG.
- Identify biomarkers in EEG signals that indicate motor response potential.
- Support early prognosis and personalized neurorehabilitation planning.
- Contribute to understanding brain plasticity post-stroke.

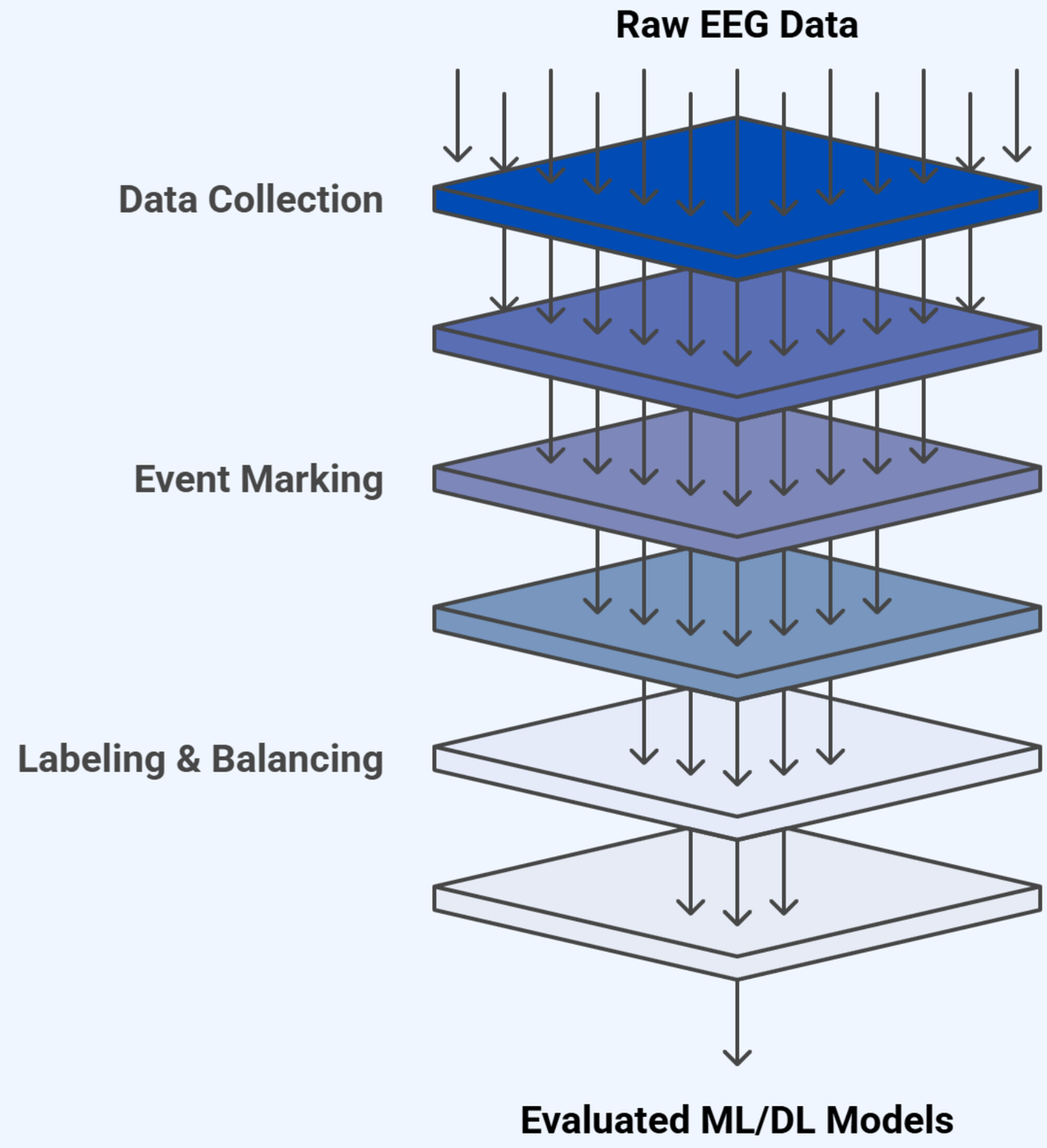
Literature Survey

sr no.	Title	Main Findings	Limitations
1.	Separated Left-Right Hemiplegia (SLR) Method for BCI-Assisted Rehabilitation	Proposed the **SLR method** to separately model left and right hemiplegia, improving prognosis prediction for **BCI-assisted rehabilitation**.	The **MCI method** used in prior studies may inaccurately model **left-right hemispheric asymmetry**, affecting **reliability and interpretability**.
2.	BCI-Based Rehabilitation System for Stroke Patients with SLR	Developed a **BCI-based rehabilitation system** that allows stroke patients with **SLR** to use **motor imagery** for controlling rehabilitation devices.	**Brain-computer interface-driven neuromuscular electrical stimulation** promotes recovery, but requires a **larger, controlled study** to validate results. - Small **sample size** and limited methodology.
3.	EEG-Based Motor Imagery BCI Robotic Rehabilitation for Arm Recovery	Found that **motor imagery BCI rehabilitation** is effective for **arm rehabilitation** after **severe post-stroke hemiparesis**.	**Small sample size** (only **26 participants**). - **Short follow-up period** (only **12 weeks**).

Literature Survey

sr no.	Title	Main Findings	Limitations
4	Brain-Computer Interface for Communication & Rehabilitation in SLR	Showed that BCIs can be used for both communication and rehabilitation, particularly for patients with SLR.	The study did not address personalized rehabilitation approaches. - More data is required to improve generalizability.
5	BCI Training with Mindfulness Therapy for Stroke Rehabilitation	Combining BCI training with mindfulness therapy improves motor function, daily activities, sleep quality, and quality of life in hemiplegic stroke patients.	Non-invasive BCI technology struggles with accurately decoding movement. - BCI training may not be fully personalized for rehabilitation needs. - Intervention group spent more time using BCI, possibly affecting results.
6	Unexpected Negative Correlation Between Brain Measures (rBSI) and Motor Function Improvement	Reported an unexpected negative correlation between regional brain symmetry index (rBSI) and motor function improvement, requiring further investigation.	**More research is needed to understand the underlying mechanisms. - Unclear causal relationships between brain symmetry and recovery outcomes.**

Methodology



Architecture and Flowchart

DATA INGESTION

EEG motor data (.mat files, .eeg , .vhdr, .vmrk)

PREPROCESSING

Filtering

Epoching

Normalization

Event labeling

Reshaping

FEATURE EXTRACTION

Imbalance Handling

ADASYN

Class weights

Statistical

Hjorth parameters

Wavelet Features

Band Power

MODEL TRAINING

Traditional

- SVM
- RF
- XGBoost

Deep Learning

- LSTM
- CNN

Evaluation on patient Data

- Accuracy
- F1 Score
- Precision
- Recall

Visualization

ROC curve

Confusion Matrix

Classification reports

Model comparisons

Implementation

Categories

Datasets Used:

1. BCI Competition IV
2. Eliptical seizure
3. Index of /pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/EEG_MPILMBB_LEMON/EEG_Preprocessed_BIDS_ID/EEG_Preprocessed/
4. BNCI horizon 2020 , P300 speller with ALS patients

Why Use 5 Different Models?

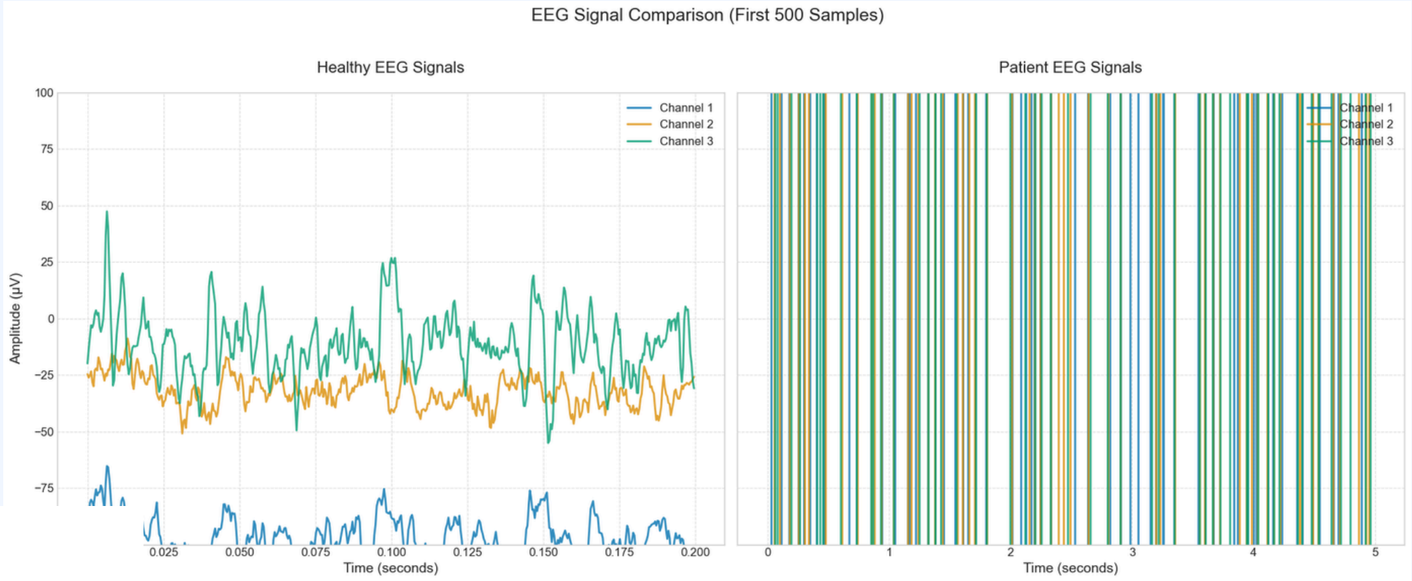
Each model excels at different tasks (e.g., CNNs for images, LSTMs for text).

Ensembles (like Random Forest + XGBoost) often outperform single models.

- Structured data? → XGBoost.
- Images? → CNN.
- Time series? → LSTM.

Results

Fig.1 Response difference between healthy participants and patients



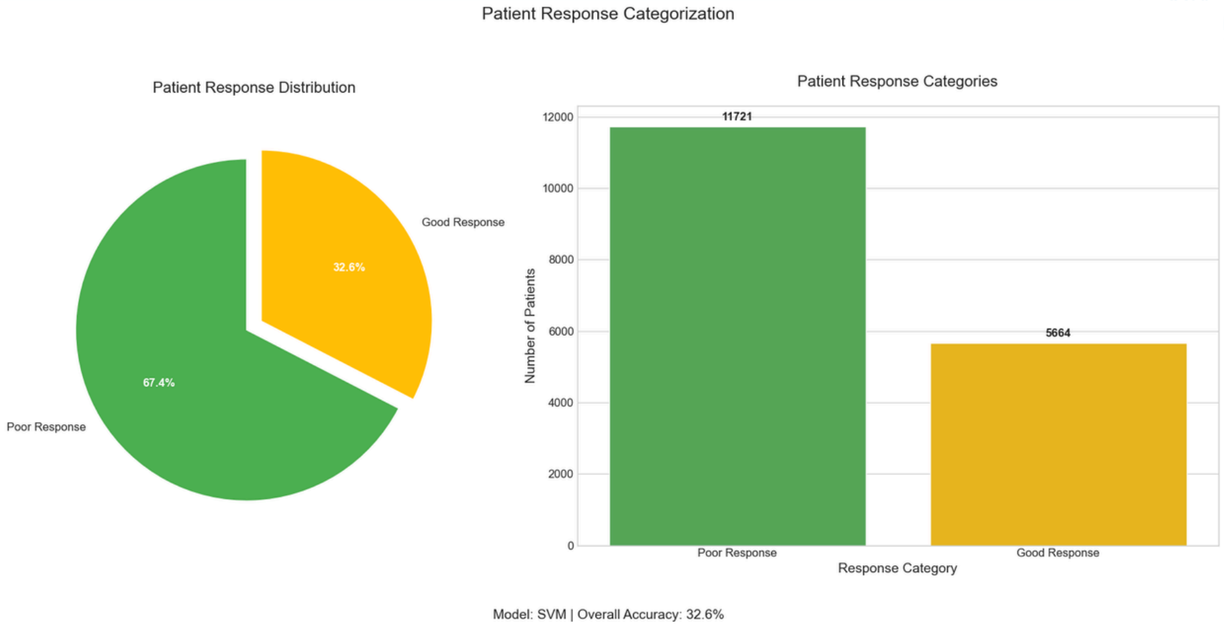
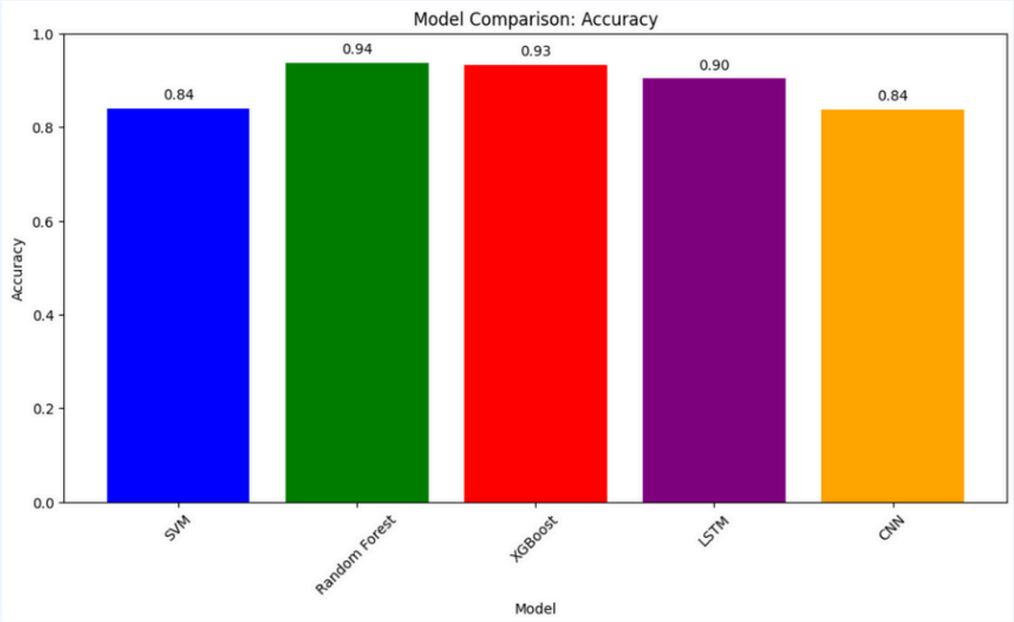
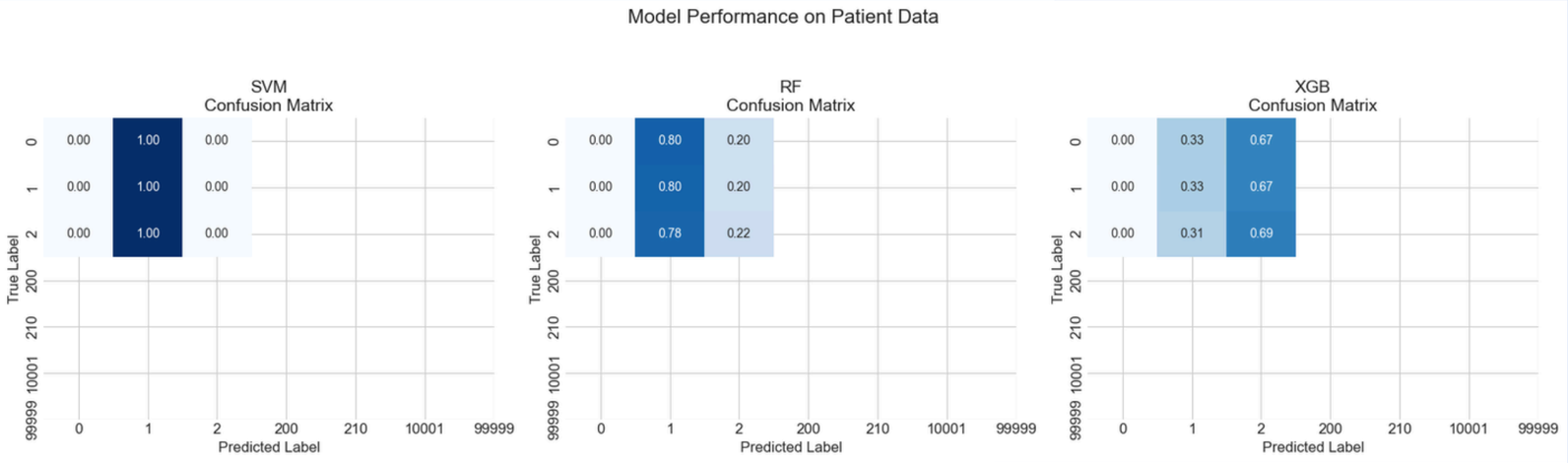


Fig.2 Response Distribution

Comparative Analysis of Models





Future Scope

- Real-time EEG monitoring for ICU and neurorehab use.
- Clinical diagnostics support for detecting brain abnormalities.
- Transfer learning to adapt models across diverse datasets.
- Explainable AI for model transparency in healthcare.
- Hybrid models combining signal processing + deep learning.
- Edge device deployment using lightweight neural networks.
- Multi-modal fusion with EMG, fNIRS for richer analysis.

Conclusion

This project establishes a robust EEG classification pipeline trained on resting-state data from healthy individuals. By applying advanced preprocessing, feature extraction, and a combination of ML and DL models—alongside class balancing techniques like SMOTE/ADASYN and class weights—we build a strong baseline for healthy brain activity patterns. This framework can be extended for anomaly detection in clinical EEGs, aiding early diagnosis and monitoring of neurological conditions.

Don't be shy — throw your questions at us like EEG spikes, we can handle the signal!

References

References

[1] Robinson et al., "Separated Left-Right Hemiplegia Model for BCI Rehabilitation," 2022.

[2] Usman et al., "BCI-Based Neuromuscular Stimulation for Stroke-Induced Hemiplegia," 2021.

[3] Rasekhi et al., "EEG-Based Motor Imagery BCI for Post-Stroke Rehabilitation," 2020.

[4] Brown et al., "Mindfulness Therapy and BCI Training for Hemiplegic Stroke Patients," 2019.

[5] Lee et al., "Brain Symmetry Index and Motor Recovery in Stroke Rehabilitation," 2018.

References

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[1] Robinson et al., "Separated Left-Right Hemiplegia Model for BCI Rehabilitation," 2022.

[2] Usman et al., "BCI-Based Neuromuscular Stimulation for Stroke-Induced Hemiplegia," 2021.

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Thank You