Practicum Report

"Human Brain Activity Classification"

Under the Guidance
of
Dr. Monika Bansal

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DECLARATION

This is to certify that Practicum Report titled "**Human Brain Activity Classification**", for the Practicum course with AIML260 is submitted by Utsav Singhal, 02917711622, AIML-A Saarthak Bansal, 03917711622, AIML-A ,Chakshu Gupta, 05817711622, AIML-A, Dhairya Goel, 06117711622, AIML-A in partial fulfillment of the requirement for the award of degree B.Tech. in Artificial Intelligence and Machine Learning, VIPS-TC, GGSIP University, Dwarka, Delhi. It comprises of our original work. The due affirmation has been made within the report for utilizing the referenced work.

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Certificate by Supervisor

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Date: **(Signature)**

Dr. Monika Bansal

Signature of HOD **Signature of Branch Coordinator**

Acknowledgement

We would like to express my heartfelt gratitude to all those who have contributed to the successful completion of our practicum report. First and foremost, we would like to extend our deepest appreciation to our supervisor, Dr. Monika Bansal, for their constant guidance, valuable insights, and unwavering support throughout this journey. We are also indebted to the staff and faculty members of VIPS-TC, GGSIPU, Dwarka, Delhi, whose expertise and cooperation were instrumental in enhancing our learning experience. Additionally, we are grateful to our fellow students who provided us with invaluable feedback and encouragement.

(Signature of the students)

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1. Introduction

When it comes to caring for patients with neurological conditions, every moment counts. Imagine being in a hospital, where quick and accurate decisions can mean the difference between preventing harm and providing the best possible care. This is where electroencephalography (EEG) steps in as a crucial tool.EEG isn't just another medical instrument—it's like having a window into the intricate workings of the human brain, allowing doctors to monitor real-time brain activity with remarkable precision. Think of it as a guardian angel, quietly watching over patients in critical care settings, such as hospitals. With EEG recordings, healthcare professionals can uncover vital insights into neurological diseases like seizures or unusual brain activity. It's like having a detective on the case, revealing clues that help diagnose conditions and guide treatment plans tailored to each patient's needs.

In essence, EEG isn't just about data—it's about empowering caregivers to make informed decisions swiftly and confidently, ensuring that patients receive the timely attention and support they deserve. So, let's delve deeper into the world of EEG and explore how it's transforming patient care, one brainwave at a time. Epilepsy is a neurological disease characterized by rapid electrophysiological changes in the brain. More than 60 million people worldwide suffer from various types of epilepsy, especially in developing countries. Epilepsy detection is an important task in clinical research, which has stimulated extensive research into the design and diagnosis of automated seizure algorithms to develop treatment strategies. Additionally, predicting seizures may help further treatment of these patients. Scalp electroencephalography (EEG) is an important diagnostic tool for patients with epilepsy. In recent years, digital EEG monitoring systems can capture long-term EEG data of epileptic patients to identify the occurrence of abnormal events and make timely decisions. Experts detect cases of epilepsy by reading long, time-consuming electroencephalograms. Epilepsy monitoring can help professionals identify epileptic events in EEG signals.

2. Related Work

In the realm of neuroscience and machine learning, the focus is on understanding and addressing the critical issue of identifying and managing seizures and other hazardous patterns of brain activity. These patterns pose a significant risk to patients, increasing the likelihood of in-hospital mortality, especially when they persist for extended periods. To tackle this challenge, researchers have turned to Convolutional Neural Networks (CNNs), a deep learning architecture renowned for its ability to analyze grid-like structures, such as images. CNNs excel in pattern recognition tasks by capturing spatial relationships effectively. However, while they are adept at capturing local spatial patterns, they may struggle with the intricate spatial dynamics present in EEG signals. Despite their effectiveness, training complex CNNs can be resource-intensive, demanding substantial amounts of time and data. This poses challenges for real-life applications, particularly in low-resource environments. Nonetheless, studies have shown promising results using CNN approaches in seizure detection and classification. Researchers have explored various techniques to enhance CNN performance in EEG analysis. Some have employed transfer learning models, leveraging pre-trained CNNs to improve classification accuracy. Others have experimented with transforming EEG time series into spectrograph images to facilitate CNN-based analysis. Beyond CNNs, Recursive Neural Networks (RNNs) have emerged as another valuable tool in EEG analysis. RNNs, particularly Long Short-Term Memory (LSTM) networks, are adept at capturing temporal dependencies in sequential data. They have been successfully employed in seizure prediction and detection tasks, offering a powerful means of extracting high-level representations from EEG signals. Recent studies have demonstrated the effectiveness of LSTM models in identifying different patterns in EEG signals, showcasing their potential for both invasive and non-invasive recordings. These advancements underscore the importance of leveraging cutting-edge machine learning techniques to improve our understanding and management of neurological conditions, ultimately enhancing patient outcomes in critical care settings.

3. Problem Statement and Objective

Our primary objective is to develop an advanced machine learning system that utilizes EEG signals to enhance patient care in hospital settings by:

- Detecting various forms of hazardous brain activity.
- Categorizing detected abnormalities accurately and efficiently.
- Providing timely alerts to healthcare professionals regarding critical neurological distress indicators.

By building this advanced machine learning system, we aim to provide healthcare professionals with a powerful ally in their efforts to ensure patient safety and well-being. With accurate and timely detection of hazardous brain activity, we can enable quicker response times and more effective treatment strategies, ultimately improving outcomes for patients in critical care.

4. Design Phase

4.1 Software Requirements:

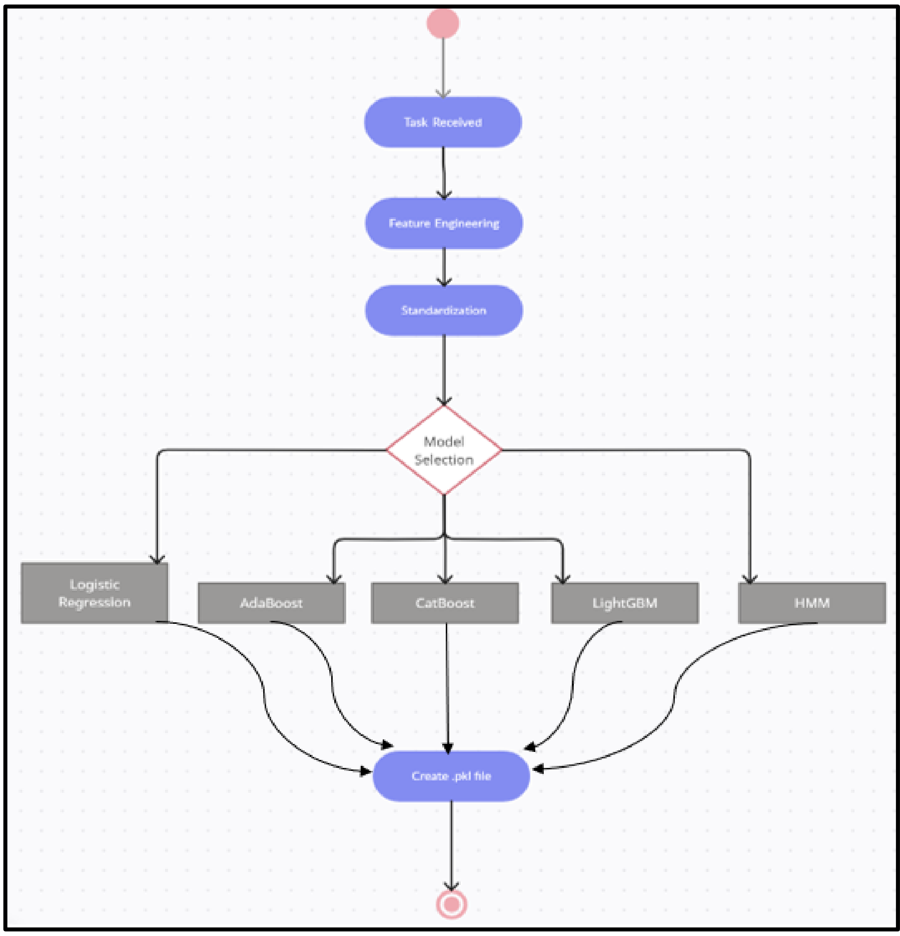
1) Python (programming language)

2) Jupyter Notebook or JupyterLab (for interactive development)

3) IDEs (Integrated Development Environments) such as PyCharm, Spyder, or VSCode (for code development)

4) Version Control System: Git & Github (for collaborative development and version control)

4.2 Flow Chart/Activity Diagram



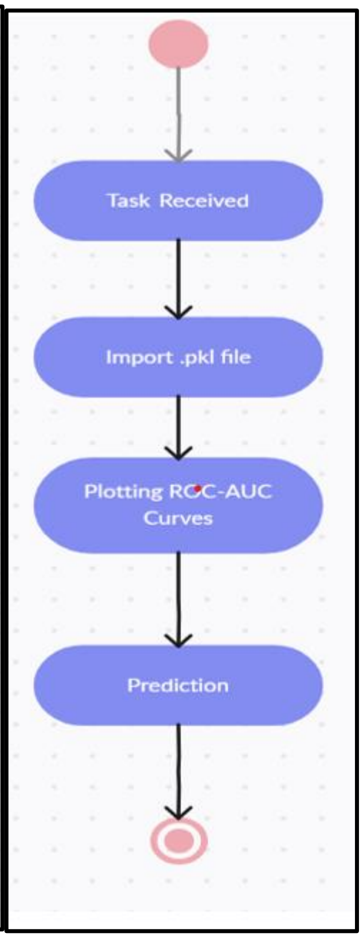


Figure I: Pre-Processing and Training

Figure II: Prediction

5. Work Done

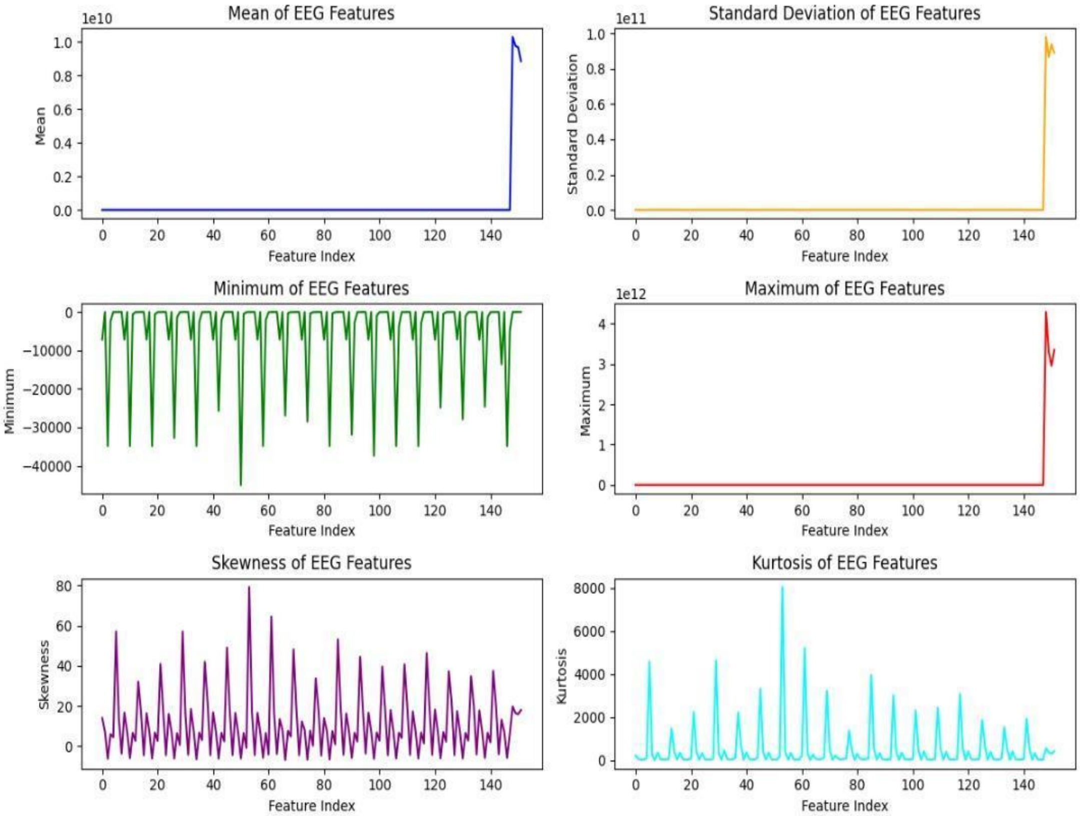


Figure III: EDA & Feature Engineering

Table I: Dataset description of given by Critical Care EEG Monitoring Research Consortium (CCEMRC)

S.No	Column	Non-Null	Count	Dtype
1	EEG_ID	29928	Non-Null	Int64
2	EEG_Sub_ID	29928	Non-Null	Int64
3	EEG_Label_Offset_Seconds	29928	Non-Null	Float64
4	Spectrogram_ID	29928	Non-Null	Int64
5	Spectrogram_Sub_ID	29928	Non-Null	Int64
6	Spectrogram_Label_Offset_Seconds	29928	Non-Null	Float64
7	Label_Id	29928	Non-Null	Int64
8	Patient_Id	29927	Non-Null	Float64
9	Expert_Consensus	29927	Non-Null	Object
10	Seizure_Vote	29927	Non-Null	Float64
11	LPD_Vote	29927	Non-Null	Float64
12	GPD_Vote	29927	Non-Null	Float64
13	LRDA_Vote	29927	Non-Null	Float64
14	GRDA_Vote	29927	Non-Null	Float64
15	Other_Vote	29927	Non-Null	Float64

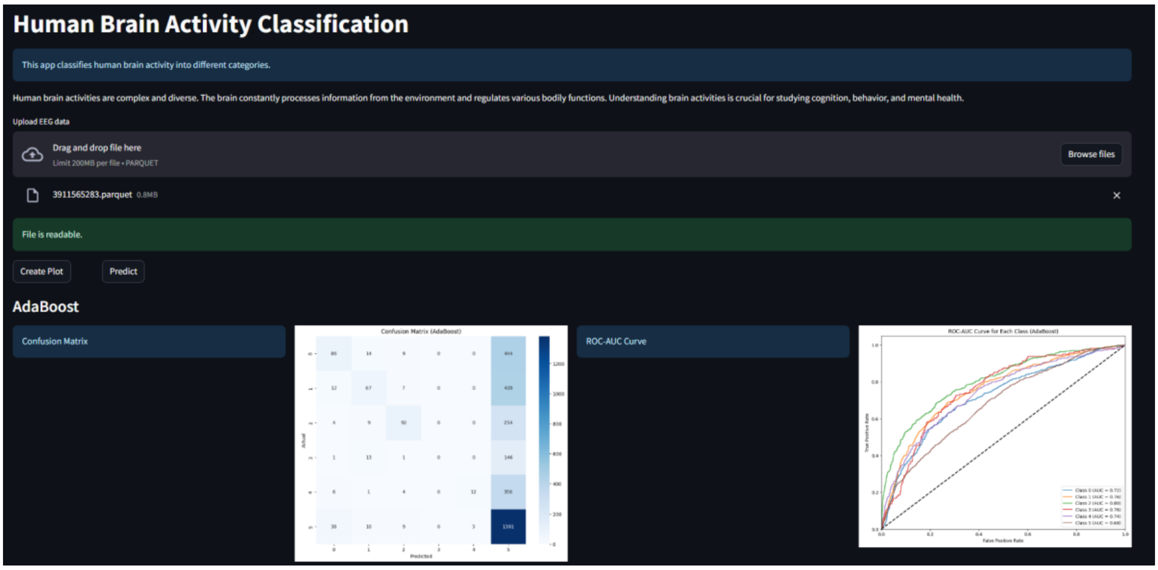


Figure IV: Frontend

6. Results

Light GBM				
	Precision	**Recall**	**F1-Score**	**Support**
Seizure	0.59	0.48	0.53	553
LPD	0.73	0.6	0.66	525
GPD	0.85	0.55	0.67	359
LRDA	0.73	0.2	0.31	161
GRDA	0.66	0.32	0.44	379
Other	0.6	0.86	0.71	1441

XGBoost				
	Precision	**Recall**	**F1-Score**	**Support**
Seizure	**0.58**	**0.49**	**0.53**	**553**
LPD	**0.71**	**0.62**	**0.66**	**525**
GPD	**0.81**	**0.55**	**0.65**	**359**
LRDA	**0.57**	**0.24**	**0.33**	**161**
GRDA	**0.62**	**0.34**	**0.44**	**379**
Other	**0.61**	**0.84**	**0.71**	**1441**

CatBoost				
	Precisin	**Recall**	**F1-Score**	**Support**
Seizure	**0.6**	**0.44**	**0.51**	**553**
LPD	**0.74**	**0.58**	**0.65**	**525**
GPD	**0.84**	**0.53**	**0.65**	**359**
LRDA	**0.73**	**0.2**	**0.32**	**161**
GRDA	**0.62**	**0.27**	**0.38**	**379**
Other	**0.58**	**0.88**	**0.7**	**1441**

AdaBoost				
	Precision	**Recall**	**F1-Score**	**Support**
Seizure	**0.59**	**0.16**	**0.25**	**553**
LPD	**0.59**	**0.13**	**0.21**	**525**
GPD	**0.75**	**0.26**	**0.38**	**359**
LRDA	**0**	**0**	**0**	**161**
GRDA	**0.8**	**0.03**	**0.06**	**379**
Other	**0.46**	**0.96**	**0.62**	**1441**

Table II: Confusion Matrix

7. Conclusion

The study employed a "pattern recognition" approach to classify EEG signals recorded during testing and active cognitive states of consciousness. Various machine learning algorithms, including Logistic Regression, XGBoost, AdaBoost, LightGBM, and CatBoost, were utilized to classify different EEG patterns such as Seizure, Generalized Periodic Discharges (GPD), Lateralized Rhythmic Delta Activity (LRDA), Generalized Rhythmic Delta Activity (GRDA), and other patterns.

The classification results obtained from the mentioned algorithms showed variations in performance metrics including recall, precision, and F1-score. However, these results were not consistently accurate across all decomposition levels. To validate the proposed approach, experimental results were evaluated using KL Divergence Evaluation loss metrics. Despite some limitations in the study, such as the need for a larger dataset to enhance robustness and the relatively easier separation of EEG signals recorded during cognitive tasks, the findings suggest promising potential for the method's application to clinical datasets.

In summary, while the study demonstrated promising results, further research with larger datasets and consideration of additional factors are recommended for more comprehensive validation and application of the proposed method in EEG signal classification.

8. Future Scope of Work

The approach used in the study offers exciting possibilities for future applications in neurology and research. One potential avenue is the development of wearable devices capable of detecting seizures in real-time by analyzing EEG signals and patterns. These devices could send alerts to both patients and doctors, enabling timely intervention and treatment.

By using wearable technology combined with advanced algorithms, doctors could monitor patients remotely and accurately identify seizure events as they happen. This proactive approach could improve patient safety and help reduce the severity and duration of seizures.

Integrating cloud-based platforms for storing and accessing patients' medical histories could further enhance seizure management. By uploading and maintaining comprehensive medical records in secure cloud repositories, doctors could gain valuable insights into each patient's condition over time. This data would enable more informed decision-making, personalized treatment plans, and continuous monitoring of disease progression.

Moreover, cloud-based platforms facilitate seamless communication between patients, caregivers, and medical professionals. Patients could easily share their data with doctors, enabling remote consultations and proactive interventions based on real-time insights. This integrated approach promotes patient engagement and empowers individuals to take an active role in managing their health.

In summary, the integration of wearable devices for seizure detection and cloud-based platforms for storing medical data holds significant promise for improving patient outcomes in neurology. By leveraging advancements in technology and data analytics, healthcare providers can deliver timely interventions, personalized care, and continuous monitoring, ultimately enhancing the quality of life for individuals living with epilepsy and other neurological disorders.

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