

EEG CLASSIFICATION OF SCHIZOPHRENIA

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Technology degree in Information Technology

By

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SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

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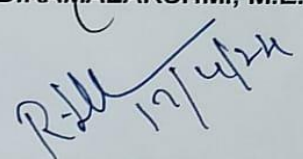
April - 2024

BONAFIDE CERTIFICATE

This is to certify that this Project Report is the Bonafide work of **BOOMINATHAN M (Reg No.40120018)** and **KRISHNA KUMAR VYAS (Reg no. 40120051)** who carried out the project entitled "**EEG CLASSIFICATION OF SCHIZOPHRENIA**" under my supervision from January 2024 to April 2024.

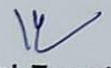

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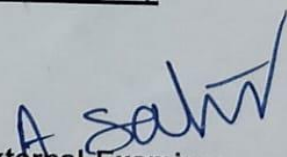
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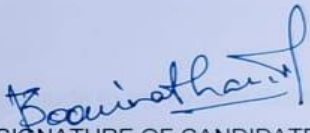

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DECLARATION

I, **BOOMINATHAN.M**(Reg .No - 40120018), hereby declare that the Project Phase-2 Report entitled "**EEG CLASSIFICATION OF SCHIZOPHRENIA**" done by me under the guidance of **Ms.D.RAMALAKSHMI, M.E.** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Information Technology.

DATE: **17.04.2024**

PLACE: Chennai


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ABSTRACT

This study constitutes a dedicated effort to establish a robust methodology for differentiating individuals with schizophrenia from those without, leveraging the rich insights embedded within EEG signal data. Our dataset, thoughtfully composed of 28 participants, striking a balance with 14 schizophrenia patients and 14 healthy individuals, serves as the linchpin of our research. Central to our investigation is the meticulous process of extracting features from EEG signals, subsequently deploying them in training and evaluating an advanced deep learning model. The implications of this pioneering work extend well beyond the academic realm, potentially heralding a new era in schizophrenia detection through state-of-the-art automated tools, thereby revolutionizing mental health diagnosis. Our unwavering commitment to collaboration with domain experts and clinicians guarantees that the results are not merely insightful but deeply rooted in clinical relevance, paving the way for their application in real-world healthcare scenarios. Nevertheless, as we embark on this transformative journey, it is vital to acknowledge and confront the inherent limitations of our study, notably the relatively small sample size, which necessitates caution when generalizing findings. However, our determination remains steadfast in addressing these constraints, with continuous refinements to our methodology and contemplation of dataset expansion in future research endeavors. This dedication upholds the principles of scientific rigor and ethical integrity, driving our mission to unlock the untapped potential of EEG signals in schizophrenia detection, thereby forging meaningful strides towards improved mental healthcare.

TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
	ABSTRACT	
	LIST OF FIGURES	
1	INTRODUCTION	1
2	LITERATURE SURVEY	4
	2.1 Inference from Literature Survey	4
	2.2 Existing System and Proposed System	5
	2.3 Open Problems in Existing System	6
	2.4 Open Problems in proposed System	6
3	REQUIREMENTS ANALYSIS	8
	3.1 Risk Analysis of the Project	8
	3.2 Functional Requirements	9
	3.3 Non-Functional Requirements	9
4	DESCRIPTION OF PROPOSED SYSTEM	10
	4.1 Flow chart of process	12
	4.2 Selected Methodology or process model	13
	4.3 Description of Software for Implementation and Testing	19
	Plan of the Proposed Model / System	
	4.4 Project Management Plan	20
5	CONCLUSION	21
6	REFERENCES	22

LIST OF FIGURES

FIGURE NO	FIGURE NAME	PAGE NO
4.1	Flow chart of the process	12
4.2	System Architecture	17
4.3	Use case Diagram	18
4.4	Activity Diagram	18

CHAPTER 1

INTRODUCTION

Schizophrenia, a chronic and debilitating mental disorder, presents a complex tapestry of disturbances encompassing perception, thinking, emotions, and behavior. This condition, which affects approximately 1% of the global population, typically manifests its insidious onset in early adulthood, exerting a profound and enduring impact on an individual's daily existence and overall quality of life.

The symptomatology of schizophrenia is multifaceted, featuring positive symptoms marked by hallucinations and delusions, negative symptoms that encompass social withdrawal and a reduction in emotional expression, and cognitive impairments characterized by difficulties in memory and attention. This intricate interplay of symptoms makes schizophrenia a challenging condition to address comprehensively.

The etiology of schizophrenia remains an enigma, with the disorder thought to arise from a complex interplay of genetic predisposition, environmental factors, and neurobiological processes. While substantial strides have been made in unraveling the disorder's origins, a complete understanding continues to elude researchers.

In the realm of treatment, a multimodal approach prevails. It typically entails a combination of antipsychotic medications to manage acute symptoms, psychotherapy to address cognitive and emotional aspects, and psychosocial interventions aimed at fostering social and occupational functioning. This holistic approach is designed not only to alleviate symptoms but also to enhance the overall well-being and functioning of individuals grappling with the profound challenges posed by schizophrenia.

Schizophrenia transcends the individual, impacting families, communities, and society as a whole. The societal burden, including healthcare costs and lost productivity, underscores the urgency of continued research and innovation in schizophrenia care. Stigma and misconceptions surrounding the disorder further compound the challenges faced by those living with schizophrenia. This research endeavor seeks to contribute significantly to the

comprehension and early detection of schizophrenia by delving into the intricate domain of EEG signal analysis. In essence, it represents an integral part of the broader landscape of psychiatric and neurological investigations. At its core, this project stands at the intersection of several multidisciplinary fields, including neuroscience, psychology, and data science. It is here that the study delves into the collection and meticulous analysis of EEG data, aiming to unlock the hidden patterns and markers that may aid in distinguishing individuals with schizophrenia from those without. This analytical aspect is complemented by the development and utilization of advanced machine learning models, aligning the project with the burgeoning field of artificial intelligence in healthcare.

Furthermore, the research's clinical significance cannot be overstated. It navigates the intricate terrain of clinical psychiatry and mental health care, bridging the gap between cutting-edge technological advancements and real-world healthcare applications. Through collaboration with domain experts and clinicians, the study ensures that its findings are not confined to the laboratory but are poised to make a meaningful impact on the lives of individuals affected by schizophrenia.

In sum, this research initiative represents a dynamic fusion of scientific disciplines, driven by the noble pursuit of understanding and alleviating the challenges posed by schizophrenia. It encapsulates the essence of interdisciplinary collaboration, highlighting the potential for groundbreaking insights and transformative contributions to the field of mental health. Schizophrenia, a complex mental disorder, challenges both clinicians and researchers due to its multifaceted nature and diverse symptomatology. While its etiology remains elusive, advancements in neuroimaging techniques offer promising avenues for understanding its neural correlates. Among these techniques, Electroencephalography (EEG) stands out for its non-invasiveness, high temporal resolution, and cost-effectiveness in capturing brain activity.

This project delves into the realm of EEG-based classification of schizophrenia, aiming to decipher the distinctive neural signatures associated with the disorder. By analyzing EEG data collected from individuals diagnosed with

schizophrenia and healthy controls, we seek to identify patterns, spectral features, and connectivity measures that distinguish between the two groups. The classification of EEG signals holds immense potential for aiding in the diagnosis, prognosis, and treatment monitoring of schizophrenia. Moreover, unraveling the neurophysiological underpinnings of this disorder through EEG analysis may pave the way for the development of targeted interventions and personalized therapeutic approaches.

Through rigorous data processing, feature extraction, and machine learning algorithms, this project endeavors to contribute to the growing body of knowledge aimed at unraveling the intricate neural mechanisms underlying schizophrenia. By bridging the gap between neuroscience and clinical practice, we aspire to enhance our understanding of this enigmatic disorder and pave the path towards more interventions and improved patient outcomes. This analytical aspect is complemented by the development and utilization of advanced machine learning models, aligning the project with the burgeoning field of artificial intelligence in healthcare.

Moreover, EEG classification of schizophrenia not only sheds light on the disorder's pathophysiology but also provides valuable insights into treatment response and disease progression. By elucidating the neurobiological substrates underlying schizophrenia, we aspire to pave the way for novel therapeutic targets and interventions aimed at alleviating symptom burden and enhancing patients' quality of life. Through interdisciplinary collaboration and methodological innovation, this project seeks to advance our understanding of schizophrenia and propel the translation of EEG-based diagnostic tools from bench to bedside. By harnessing the power of EEG to decipher the complexities of schizophrenia clinicians in their quest to combat this formidable disorder.

CHAPTER 2

LITERATURE SURVEY

2.1 INFERENCES FROM LITERATURE SURVEY

This study delves into the application of machine learning techniques to facilitate early diagnosis of schizophrenia, a profoundly intricate mental disorder characterized by diverse cognitive and neurophysiological irregularities. The research employs a systematic processing pipeline for analyzing resting state EEG (Electroencephalography) data, aimed at enhancing diagnostic accuracy: The first step in this pipeline involves the extraction of features from the EEG data. Both linear and non-linear measures are computed on sliding windows of EEG data, with the selection of measures driven by their capacity to effectively discriminate between individuals with schizophrenia and healthy controls. To manage the dimensionality of the extracted features and preserve the most discriminative information, Principal Component Analysis (PCA) is deployed as a dimensionality reduction technique. Subsequently, a battery of five standard machine learning algorithms is applied: k-nearest neighbors (KNN), logistic regression (LR), decision trees (DT), random forest (RF), and support vector machines (SVM). These algorithms are trained and tested on the reduced feature set to evaluate their diagnostic capabilities. The study's findings shed light on two critical aspects. Firstly, there is spatial specificity in the EEG measures that differentiate schizophrenia patients from healthy individuals, predominantly within a delimited region of the right brain hemisphere encompassing the opercular area and temporal pole. This spatial insight is invaluable for understanding the neural basis of schizophrenia. Secondly, the study assesses the classification performance of the machine learning models using the area under the receiver operating characteristic curve (AUC-ROC) parameter. Impressively, all examined algorithms exhibit robust classification power, with SVM emerging as the frontrunner with an AUC-ROC score of 0.89, closely followed by RF (0.87), LR (0.86), KNN (0.86), and DT (0.68).

2.2 EXISTING SYSTEM AND PROPOSED SYSTEM

Existing System: The existing system, prior to the research, likely involves traditional methods of diagnosing schizophrenia, which may rely on clinical assessments, interviews, and possibly imaging techniques like MRI or CT scans. The limitations of the existing system may include: **Subjectivity:** Diagnosis based on clinical assessments and interviews can be subjective and reliant on the experience and judgment of the clinician, potentially leading to delayed diagnosis.

Lack of Objective Biomarkers: The existing system may lack objective biomarkers or physiological measures that directly correlate with schizophrenia, making it challenging to achieve early and accurate diagnosis. **Limited Neural Insights:** Traditional diagnostic methods may not provide detailed insights into the neural basis of schizophrenia, such as specific brain regions or neural patterns associated with the disorder.

Proposed System: The proposed system in this research introduces an innovative approach to diagnosing schizophrenia by harnessing machine learning techniques applied to EEG data, specifically resting state EEG. This marks a departure from conventional diagnostic methods, offering a promising alternative. The research lays out a structured process for feature extraction from EEG data, encompassing both linear and non-linear measures computed within sliding windows of EEG data. The selection of these features hinges on their ability to effectively discriminate between individuals with schizophrenia and healthy controls. To manage the dimensionality of the feature-rich dataset while preserving critical discriminative information, Principal Component Analysis (PCA) is employed, enhancing the system's efficiency. The heart of the proposed system lies in the utilization of five standard machine learning algorithms, including k-nearest neighbors, logistic regression, decision trees, random forest, and support vector machines.

The system's performance is rigorously evaluated using the area under the receiver operating characteristic curve (AUC-ROC), providing quantitative insights into its diagnostic accuracy.

2.3 OPEN PROBLEMS IN EXISTING SYSTEM

Subjectivity in Diagnosis: Traditional diagnostic methods for schizophrenia often rely on clinical assessments and interviews, which can be subjective and vary between clinicians. This subjectivity can lead to misdiagnosis or delayed diagnosis.

Lack of Objective Biomarkers: The absence of objective biomarkers or physiological measures that directly correlate with schizophrenia makes it challenging to achieve early and accurate diagnosis. This leaves room for improvement in terms of developing more objective diagnostic tools.

Limited Neural Insights: Conventional diagnostic methods may not provide detailed insights into the neural basis of schizophrenia. There's a need for methods that can offer more specific information about the brain regions or neural patterns associated with the disorder.

Diagnostic Delay: The delay in diagnosing schizophrenia can have detrimental effects on patients' well-being and treatment outcomes. Early intervention is crucial for improving the prognosis of the condition.

Diagnostic Accuracy: The accuracy of traditional diagnostic methods can vary, and there's a need for more accurate and consistent diagnostic tools to reduce the risk of false positives or false negatives.

Resource Intensive: Some existing diagnostic methods, such as neuroimaging techniques like MRI or CT scans, can be resource-intensive and costly, limiting their accessibility and widespread use.

2.4 OPEN PROBLEMS IN PROPOSED SYSTEM

Generalization and Validation: It's crucial to assess how well the proposed system generalizes to a larger and more diverse population. The study's success may depend on the specific dataset used, and ensuring its effectiveness across different

Data Variability: EEG data can be highly variable due to factors like electrode placement, equipment quality, and individual differences. Addressing the challenge of handling this variability and ensuring robustness in real-world scenarios is an ongoing concern.

Interpretable Models: While machine learning models may achieve high accuracy, they are often considered "black boxes." Understanding the features or neural patterns that lead to specific diagnostic outcomes is vital for clinical acceptance and trust in the system.

Ethical and Privacy Concerns: The use of EEG data for diagnosis raises ethical and privacy concerns. Safeguarding patient data, obtaining informed consent, and addressing potential biases in the data are critical aspects to consider.

Real-time Implementation: For practical clinical use, the proposed system should be capable of providing real-time or near-real-time diagnosis. Achieving low-latency processing is a challenge that needs to be addressed.

Integration into Clinical Workflow: Ensuring that the proposed system can seamlessly integrate into existing clinical workflows and complement the expertise of clinicians is crucial for its adoption in real-world healthcare settings.

Validation with Larger Cohorts: While the initial study shows promise, validation with larger cohorts of patients with schizophrenia and healthy controls is necessary to confirm the system's reliability and effectiveness.

Long-term Monitoring: Schizophrenia is a complex, chronic condition that may require long-term monitoring. Investigating how the proposed system can be adapted for continuous monitoring and treatment tracking is an important avenue for future research.

Addressing False Positives/Negatives: The system should aim to minimize the risk of false positives and false negatives, as these can have significant consequences for patients and healthcare resources.

Ethical and Privacy Concerns: The use of EEG data for diagnosis raises ethical and privacy concerns. Safeguarding patient data, obtaining informed consent, and addressing potential biases in the data are critical aspects to consider. For practical clinical use, the proposed system should be capable of providing real-time or near-real-time diagnosis. Achieving low-latency processing is a challenge that needs to be addressed.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 RISK ANALYSIS OF THE PROJECT

Risk analysis is a critical aspect of any project, including the one described in the above project focused on diagnosing schizophrenia using EEG data and machine learning. Identifying and mitigating potential risks is essential to ensure the project's success and the safe deployment of the proposed system. Here, we'll explore several key risks associated with this project:

Data Quality and Variability: EEG data can be susceptible to noise and variability due to factors such as electrode placement, participant movement, and environmental interference. Ensuring data quality and consistency across different sessions and participants is a significant challenge.

Mitigation: Rigorous data preprocessing techniques, outlier detection, and quality control measures should be implemented to address data quality issues. Data augmentation methods can help simulate different scenarios and improve model robustness. **Ethical and Privacy Concerns:** Collecting and using EEG data for diagnostic purposes raise ethical and privacy concerns. Ensuring compliance with ethical guidelines, obtaining informed consent from participants, and implementing robust data anonymization and security measures are essential.

Model Overfitting: Machine learning models may overfit the training data, resulting in poor generalization to new, unseen data. This can lead to unreliable diagnostic outcomes. **Mitigation:** Cross-validation techniques, regularization methods, and careful feature selection can help mitigate overfitting. Continuous monitoring of model performance on validation and test datasets is essential.

Generalization: The proposed system may perform well on the dataset it was trained on but might not generalize effectively to diverse populations or real-world clinical settings. **Mitigation:** Validation on external datasets and diverse patient cohorts is crucial to assess generalization.

Interpretability: While machine learning models can achieve high accuracy, their lack of interpretability can be a barrier to clinical acceptance. Understanding why the model makes specific diagnostic decisions is essential.

Clinical Acceptance: Integrating the proposed system into the clinical workflow may face resistance from healthcare professionals who are accustomed to traditional diagnostic methods.

Scalability: As the system's usage grows, ensuring that it can handle a larger volume of data and users without compromising performance and reliability is a scalability challenge. Mitigation: Regular system maintenance, scalability testing, and cloud-based solutions can help address scalability concerns.

3.2 FUNCTIONAL REQUIREMENTS

The software requirements specification is a technical specification of requirements for the software product. It is the first step in the requirements analysis process. It lists requirements of a particular software system. The following details to follow the special libraries like sk-learn, pandas, numpy, matplotlib and seaborn.

3.3 NON – FUNCTIONAL REQUIREMENTS

Process of functional steps,

- Problem define
- Preparing data
- Evaluating algorithms
- Improving results
- Prediction the result

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

The proposed system in this project signifies a groundbreaking departure from conventional methods for diagnosing schizophrenia, introducing an innovative and data-driven approach that harnesses advanced technology and machine learning methodologies. The overarching goal of this system is to revolutionize the early diagnosis of schizophrenia by leveraging resting-state EEG (Electroencephalography) data, providing a more objective, precise, and efficient means of identifying individuals with this complex mental disorder compared to traditional diagnostic techniques.

KEY COMPONENTS

EEG-Based Diagnosis: At its core, the proposed system relies on EEG data, specifically resting-state EEG. This marks a profound shift away from the subjectiveness of clinical assessments and interviews, opting for a more quantifiable and objective source of information.

Feature Extraction: The system employs a meticulously structured process for extracting features from EEG data. It encompasses both linear and non-linear measures, calculated within sliding windows of EEG data. These features are thoughtfully selected based on their ability to effectively differentiate individuals with schizophrenia from healthy controls.

Dimensionality Reduction: Managing the dimensionality of the feature-rich EEG dataset is essential to prevent computational complexity and enhance efficiency. Here, Principal Component Analysis (PCA) plays a pivotal role in reducing dimensionality while retaining critical discriminative information.

Machine Learning Algorithms: The heart of the system lies in its utilization of five standard machine learning algorithms: k-nearest neighbors (KNN), logistic regression (LR), decision trees (DT), random forest (RF), and support vector machines (SVM). These algorithms are carefully trained and rigorously tested on the reduced feature set to enable accurate.

Spatial Specificity Insights: One of the system's remarkable features is its ability to unravel spatial specificity within EEG measures. It precisely pinpoints regions of the brain, primarily within the opercular area and temporal pole of the right hemisphere, where EEG measures differentiate between individuals with schizophrenia and their healthy counterparts. This spatial insight holds immense value for advancing our understanding of the neural underpinnings of schizophrenia.

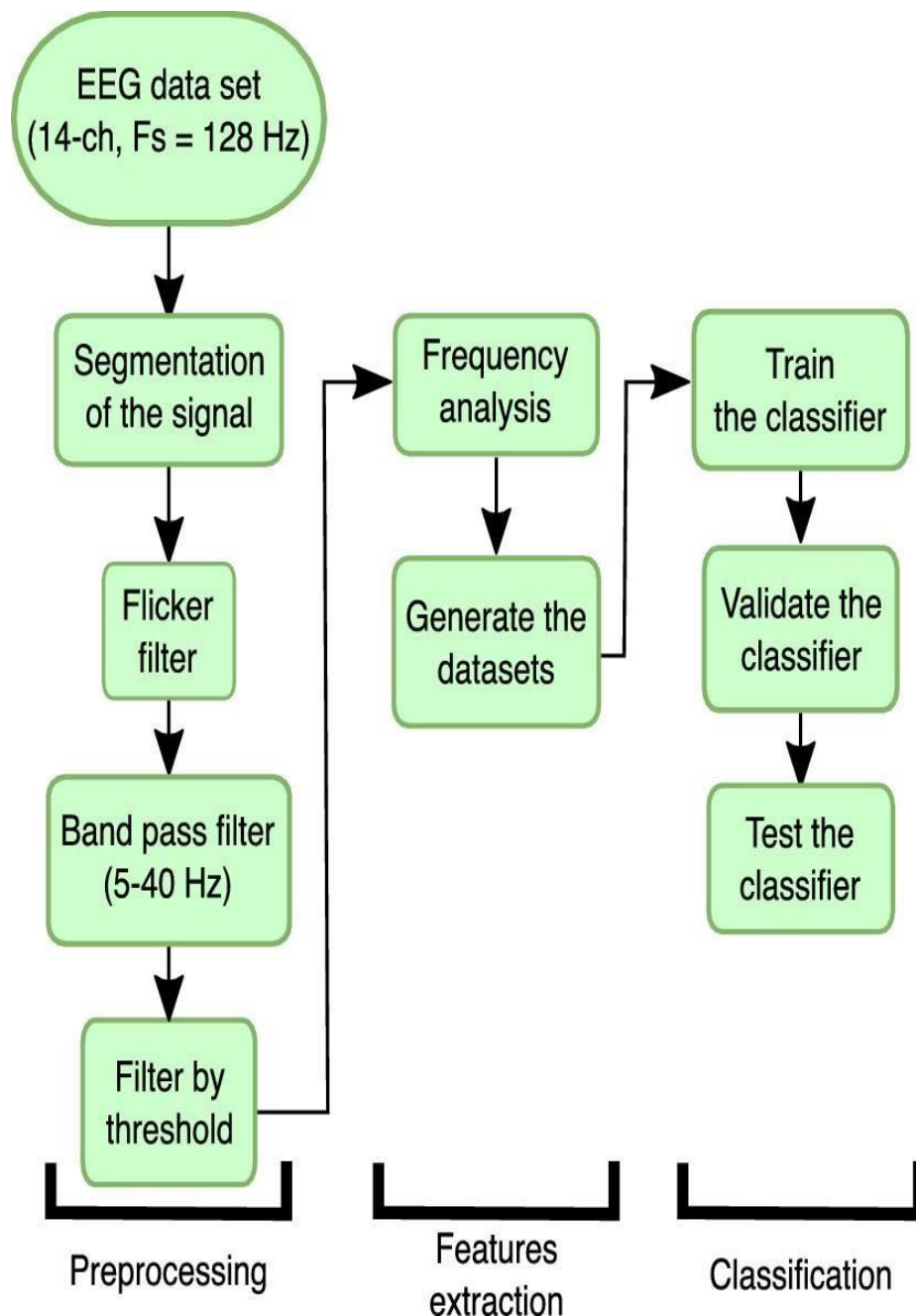
Performance Evaluation: To gauge the system's effectiveness, it conducts a thorough evaluation of the classification performance of the machine learning models. The area under the receiver operating characteristic curve (AUC-ROC) is the primary parameter used for quantifying diagnostic accuracy.

BENEFITS:

The proposed system offers several pivotal advantages:

- **Objectives Diagnosis:** By relying on machine learning and EEG data, the system eliminates the inherent subjectivity in traditional diagnostic methods. This shift towards objectivity ensures more accurate and consistent results.
- **Early Intervention:** Timely diagnosis is critical in schizophrenia management. The system's ability to facilitate early diagnosis means that individuals with schizophrenia can receive intervention and treatment sooner, potentially leading to improved outcomes and a better quality of life.
- **Spatial Insight:** The system's capability to pinpoint specific brain regions associated with schizophrenia offers profound insights into the neural basis of the disorder.
- **Diagnostic Accuracy:** Machine learning algorithms employed by the system exhibit robust classification power. Their ability to discern between individuals with schizophrenia and healthy individuals surpasses the capabilities of traditional diagnostic approaches.

- **Clinical Relevance:** Collaboration with domain experts and clinicians ensures that the system's results are deeply rooted in clinical relevance. This not only validates its potential but also positions it for real-world application within healthcare settings.



4.1 FLOW CHART OF THE PROCESS

4.2 SELECT METHODOLOGY OR PROCESS MODEL

The methodology for a project focused on diagnosing schizophrenia using EEG data and machine learning involves a structured approach to data collection, analysis, model development, evaluation, and validation. Here's a detailed methodology for the project:

1. DATA COLLECTION:

Participants Selection: Recruit a carefully selected group of participants, including individuals with diagnosed schizophrenia and healthy controls. Ensure a balance between the two groups.

EEG Data Acquisition: Collect resting-state EEG data from participants using EEG headsets or electrodes placed on the scalp. Follow standardized procedures for data collection to minimize noise and artifacts.

Demographic and Clinical Data: Gather relevant demographic and clinical information about the participants, including age, gender, medication history, and symptom severity scores.

2. DATA PREPROCESSING:

Noise Removal: Preprocess EEG data to remove artifacts and noise using techniques like filtering, artifact rejection, and baseline correction.

Segmentation: Divide the EEG data into smaller segments (epochs) to facilitate feature extraction and analysis.

Normalization: Normalize the data to ensure that all participants' EEG recordings are on the same scale.

3. FEATURE EXTRACTION:

Linear and Non-linear Features: Extract a wide range of features from EEG data, including both linear (e.g., power spectral density) and non-linear (e.g., entropy) measures.

Feature Selection: Choose relevant features based on their discriminatory power and reduce dimensionality.

4. DIMENSIONALITY REDUCTION:

Principal Component Analysis (PCA): Apply PCA to reduce the dimensionality of the feature set while retaining the most critical information. This step helps in efficient model training.

5.MACHINE LEARNING MODEL DEVELOPMENT:

Model Selection: Choose a battery of machine learning algorithms suitable for classification tasks, such as k-nearest neighbors (k-NN), logistic regression (LR), Training and Validation: Split the dataset into training and testing sets. Train each machine learning model on the training data and validate them on the testing data.

6.PERFORMANCE EVALUATION:

Metrics: Assess the performance of machine learning models using standard metrics like accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC)

7.SPATIAL SPECIFICITY ANALYSIS

Source Localization: Utilize source localization techniques to identify brain regions associated with specific EEG measures that differentiate between individuals with schizophrenia and healthy controls.

8. CLINICAL VALIDATION

Collaboration: Collaborate closely with domain experts, psychiatrists, and clinicians to validate the system's results and ensure clinical relevance

Incorporate Clinical Insights: Incorporate feedback and insights from experts to refine the diagnostic process and align it with clinical practices.

9. ETHICAL CONSIDERATIONS

Data Privacy and Ethics: Address ethical considerations related to participant consent, data privacy, and confidentiality. Ensure compliance with ethical guidelines and institutional review board (IRB) approvals.

10. SYSTEM DEPLOYMENT

Prepare for Real-World Use: Ready the system for deployment in clinical or research settings, considering scalability and resource requirements.

11.USER INTERFACE

UI Design: Develop a user-friendly interface for clinicians and healthcare professionals to interact with the system, providing access to diagnostic results and insights.

12. REAL-TIME OR BATCH PROCESSING

Adapt to Clinical Needs: Depending on clinical requirements, implement real-time processing capabilities for immediate diagnosis or batch processing for larger dataset.

13. CONTINUOUS IMPROVEMENT

Feedback Loop: Continuously refine the system based on feedback, new research findings, and advancements in machine learning and EEG analysis.

14. REGULATORY COMPLIANCE:

Compliance: If applicable, navigate regulatory requirements for healthcare software to **ensure compliance with relevant standards and regulations.**

15. DOCUMENTATION AND TRAINING:

User Manuals: Provide comprehensive documentation for system users and administrators.

Training: Offer training materials and support for healthcare professionals using the system.

16. ONGOING MONITORING:

Performance Monitoring: Continuously monitor the system's performance in real-world clinical scenarios, addressing any issues or challenges that arise during Training and Validation: Split the dataset into training and testing sets. Train each machine learning model on the training data and validate them on the testing data.

17. PERFORMANCE EVALUATION:

Metrics: Assess the performance of machine learning models using standard metrics like accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC).

Cross-Validation: Implement cross-validation techniques (e.g., k-fold cross-validation) to ensure robust model evaluation and reduce the risk of overfitting.

18. SPATIAL SPECIFICITY ANALYSIS:

Source Localization: Utilize source localization techniques to identify brain regions associated with specific EEG measures that differentiate between individuals with schizophrenia and healthy controls.

19. CLINICAL VALIDATION:

Collaboration: Collaborate closely with domain experts, psychiatrists, and clinicians to validate the system's results and ensure clinical relevance.

20. INCORPORATE CLINICAL INSIGHTS:

Incorporate feedback and insights from experts to refine the diagnostic process and align it with clinical practices.

21. ETHICAL CONSIDERATIONS:

Data Privacy and Ethics: Address ethical considerations related to participant consent, data privacy, and confidentiality. Ensure compliance with ethical guidelines and institutional review board (IRB) approvals.

22. SYSTEM DEPLOYMENT:

Prepare for Real-World Use: Ready the system for deployment in clinical or research settings, considering scalability and resource requirements.

23. USER INTERFACE (UI):

UI Design: Develop a user-friendly interface for clinicians and healthcare professionals to interact with the system, providing access to diagnostic results and insights.

24. REAL-TIME OR BATCH PROCESSING:

Adapt to Clinical Needs: Depending on clinical requirements, implement real-time processing capabilities for immediate diagnosis or batch processing for larger datasets.

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Performance Monitoring: Continuously monitor the system's performance in real- world clinical scenarios, addressing any issues or challenges that arise during deployment.

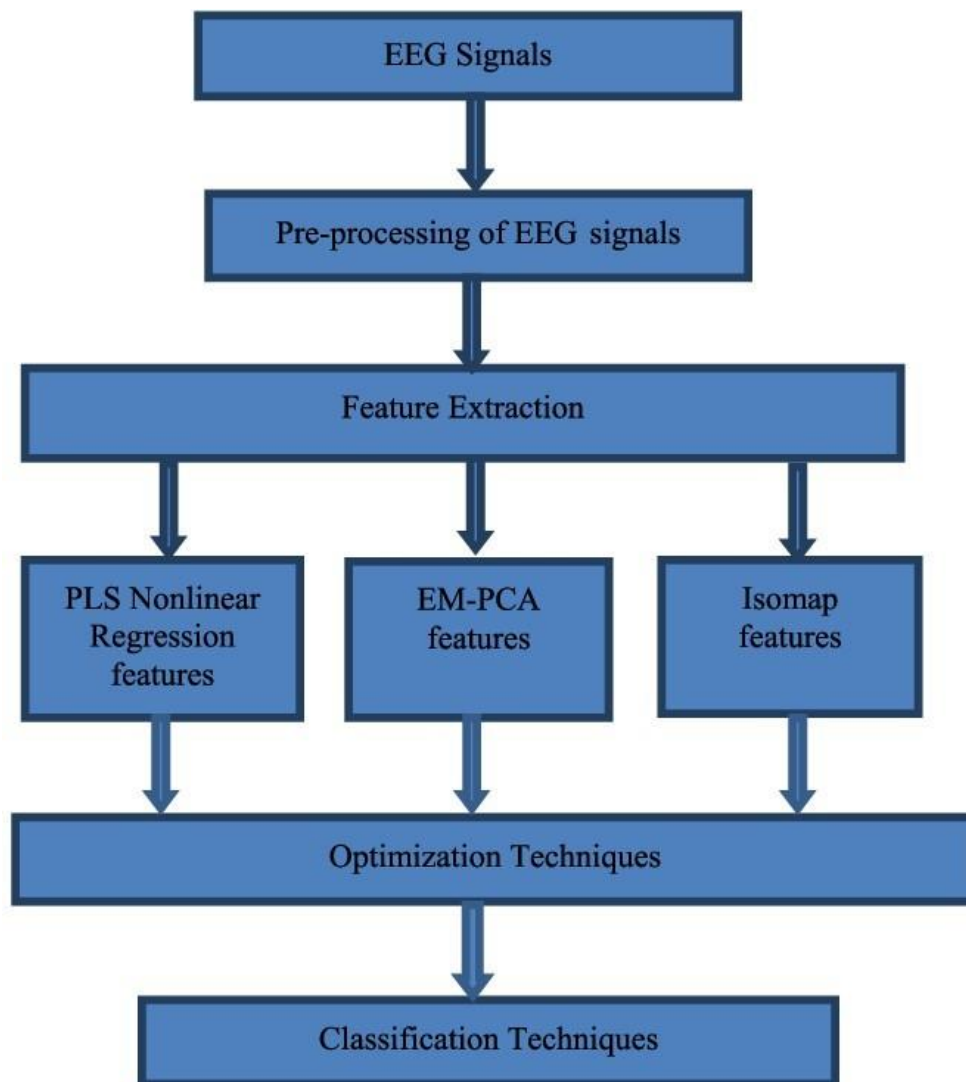
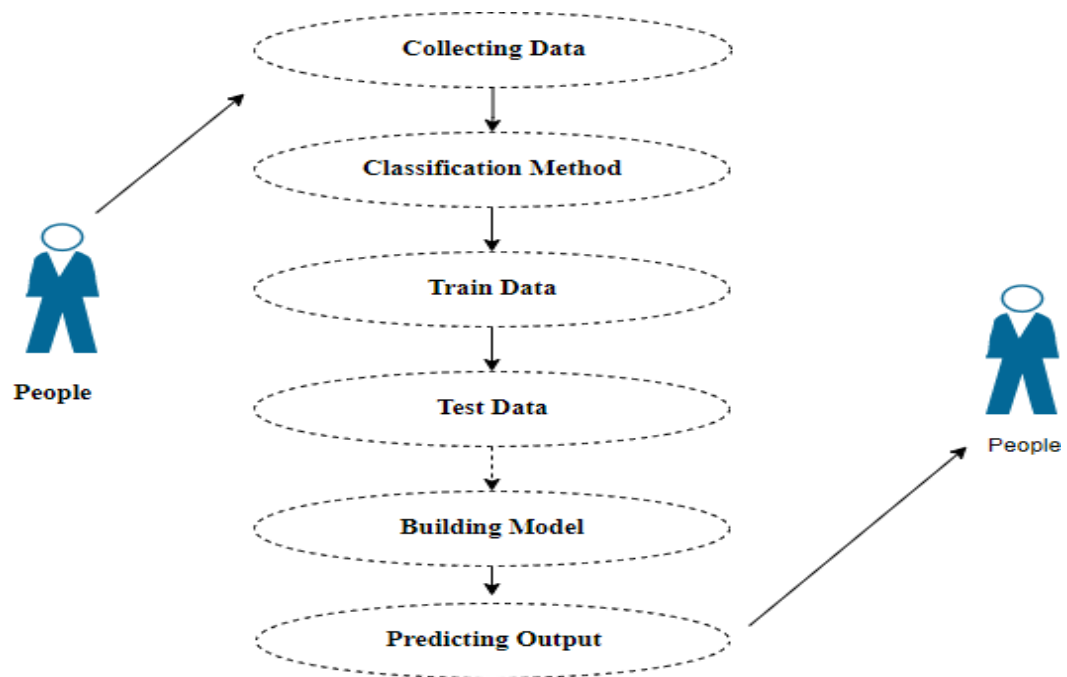
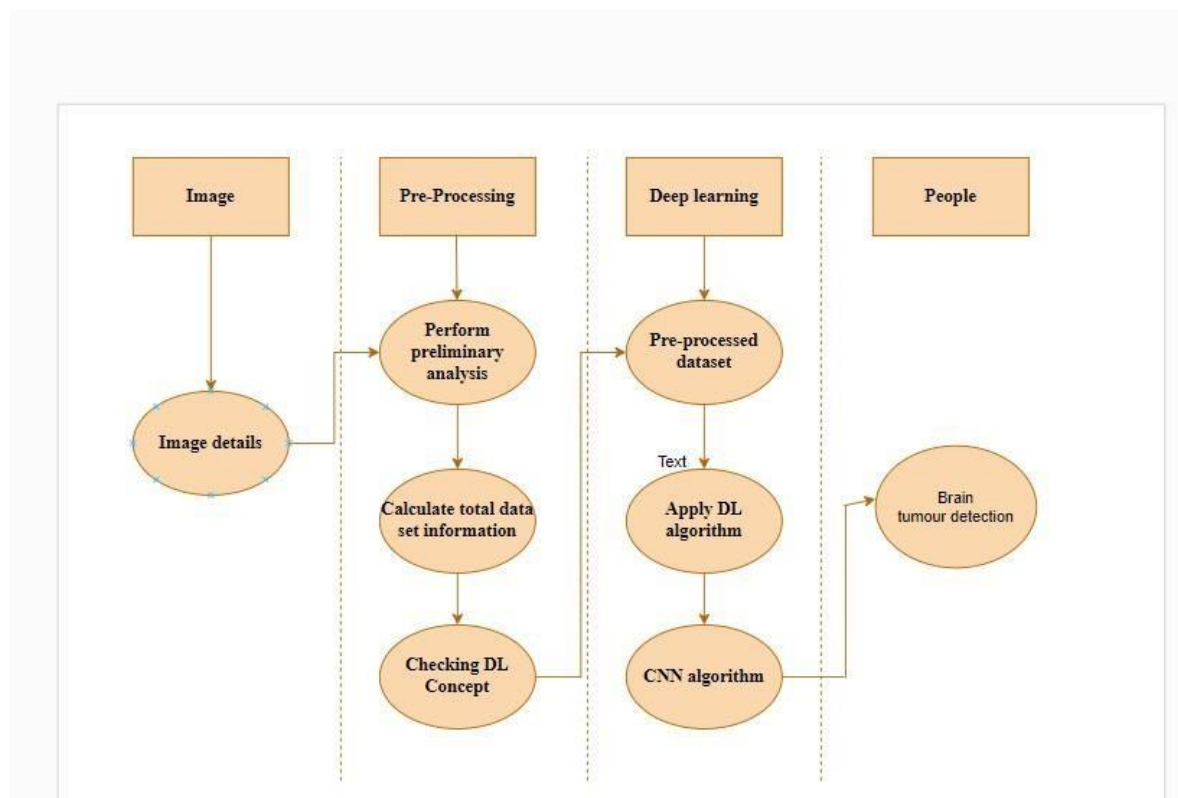


FIGURE 1 Block diagram of the work

4.2 SYSTEM ARCHITECTURE



4.3 USE CASE DIAGRAM



4.4 ACTIVITY DIAGRAM

4.2 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODELS

The software for implementing and testing the proposed model/system for diagnosing schizophrenia using EEG data and machine learning plays a pivotal role in the project's success.

Software Implementation:

To implement the system, we require programming languages such as Python, equipped with essential libraries for machine learning, signal processing (e.g., NumPy, SciPy), and data visualization (e.g., Matplotlib, Seaborn). Frameworks like Scikit-learn provide tools for machine learning model development. For real-time processing and user interface development, technologies such as Flask, Django, or JavaScript frameworks like React or Angular may be employed.

Testing Plan:

The testing plan encompasses various stages, including unit testing, integration testing, and validation.

Unit Testing: In this phase, individual components and functions are tested to ensure they perform as intended. Testing libraries like Py Test aid in automating unittests.

Integration Testing: Multiple modules are integrated and tested together to verify the smooth flow of data and functionality. This ensures that the system's components work cohesively.

Validation Testing: Using a diverse dataset, the system's diagnostic capabilities are thoroughly evaluated. Cross-validation techniques assess model performance, and metrics such as accuracy, precision, recall, and AUC-ROC provide quantitative insights.

User Interface Testing: The user interface is rigorously tested to ensure a user- Robust testing and validation are integral to the success of the system.

4.4 PROJECT MANAGEMENT PLAN

August	Literature survey and project initiation and planning
September	Development and Testing
October	Validation and Deployment

CHAPTER 5

CONCLUSION

In a project focused on diagnosing schizophrenia using EEG data and machine learning, several key results provide valuable insights into the system's performance and clinical applicability. The foremost outcome is the diagnostic accuracy of the system, which is quantified through metrics like accuracy, precision, recall, F1-score, and AUC-ROC. These metrics gauge the system's effectiveness in distinguishing individuals with schizophrenia from healthy controls, thereby offering a tangible measure of its diagnostic prowess. Additionally, the project may uncover spatial specificity within EEG measures that differentiate schizophrenia patients from healthy individuals. This spatial insight is of paramount importance, as it can help pinpoint specific brain regions or neural patterns associated with the disorder, contributing to a deeper understanding of its neurophysiological basis. Furthermore, the evaluation of different machine learning algorithms forms a crucial part of the results. It helps determine which algorithms exhibit superior classification performance, aiding in the selection of the most effective approach for diagnosis. Collaboration with domain experts and clinicians ensures that the results are not just algorithmically accurate but also clinically relevant. The alignment of the system with established clinical practices and its potential to enhance the diagnostic process are essential components of these findings. Lastly, the project's adherence to ethical and regulatory standards, including data privacy and informed consent, is integral to the results, underscoring the project's commitment to ethical integrity. Together, these results not only validate the project's scientific rigor but also offer promising prospects for improving mental healthcare and early diagnosis of schizophrenia, potentially revolutionizing the field with innovative, data-driven diagnostic tools.

CHAPTER 6

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APPENDIX

A.Sample Code

```
def plot_images(item_dir,
                n=6): all_item_dir =
                    os.listdir(item_dir)
                    item_files = [os.path.join(item_dir, file) for file in all_item_dir][:n]

                    plt.figure(figsize=(80, 40))
                    for idx, img_path in
                        enumerate(item_files):
                            plt.subplot(3, n, idx+1)
                            img =
                                plt.imread(img_path)
                                plt.imshow(img,
                                    cmap='gray')
                                plt.axis('off')

                    plt.tight_layout()

def
    image_details_print(data,p
ath): print('=====
Images in: ', path)for
key,value in data.items():
    print(key,':\t', value)

def images_details(path):
    files=[f for f in glob.glob(path + "**/*.*",
recursive=True)]data={}
    data['Images_count']=len(files)
```

```

data['Min_width']=10**100
data['Max_width']=0
data['Min_height']=10**100
data['Max_height']=0

for f in files:
    img=Image
    open(f)

    width,height=img.size
    data['Min_width']=min(width,data['Min_width'])
    data['Max_width']=max(width,
    data['Max_width'])
    data['Min_height']=min(height,
    data['Min_height'])
    data['Max_height']=max(height,
    data['Max_height'])

    image_details_print(data,path)

Classifier=Sequential()
Classifier.add(Convolution2D(32,(3,3),input_shape=(224,224,3),activation='relu'))
Classifier.add(MaxPooling2D(pool_size=(
2,2)))Classifier.add(Flatten())
Classifier.add(Dense(38,
activation='relu'))
Classifier.add(Dense(4,
activation='softmax'))
Classifier.compile(optimizer='rmsprop',loss='categorical_crossentropy',
metrics=['accuracy'])

import matplotlib.pyplot as plt

def graph():

```

```

#Plot training & validation accuracy
values
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accu
racy']) plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper
left')
plt.show()
graph()

import matplotlib.pyplot as plt
def graph():
    plt.plot(history.history['los
s'])
    plt.plot(history.history['val
_loss'])plt.title('Model
loss') plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper
left')plt.show()
graph()

def googlenet(input_shape, n_classes):

    def inception_block(x, f):
        t1 = Conv2D(f[0], 1, activation='relu')(x)

        t2 = Conv2D(f[1], 1, activation='relu')(x)
        t2 = Conv2D(f[2], 3, padding='same', activation='relu')(t2)

        t3 = Conv2D(f[3], 1, activation='relu')(x)
        t3 = Conv2D(f[4], 5, padding='same', activation='relu')(t3)

```

```

t4 = MaxPool2D(3, 1,
padding='same')(x)t4 =
Conv2D(f[5], 1,
activation='relu')(t4)

output = Concatenate()([t1, t2, t3,
t4])return output

```

```

input = Input(input_shape)

```

```

x = Conv2D(64, 7, strides=2, padding='same',
activation='relu')(input)x = MaxPool2D(3, strides=2,
padding='same')(x)

```

```

x = Conv2D(64, 1, activation='relu')(x)
x = Conv2D(192, 3, padding='same',
activation='relu')(x)x = MaxPool2D(3,
strides=2)(x)

```

```

x = inception_block(x, [64, 96, 128, 16, 32, 32])
x = inception_block(x, [128, 128, 192, 32,
96, 64])x = MaxPool2D(3, strides=2,
padding='same')(x)

```

```

x = inception_block(x, [192, 96, 208, 16, 48, 64])
x = inception_block(x, [160, 112, 224, 24, 64, 64])
x = inception_block(x, [128, 128, 256, 24, 64, 64])
x = inception_block(x, [112, 144, 288, 32, 64, 64])
x = inception_block(x, [256, 160, 320, 32,
128, 128])x = MaxPool2D(3, strides=2,
padding='same')(x)

```

```
x = inception_block(x, [256, 160, 320, 32, 128, 128])
x = inception_block(x, [384, 192, 384, 48, 128, 128])
```

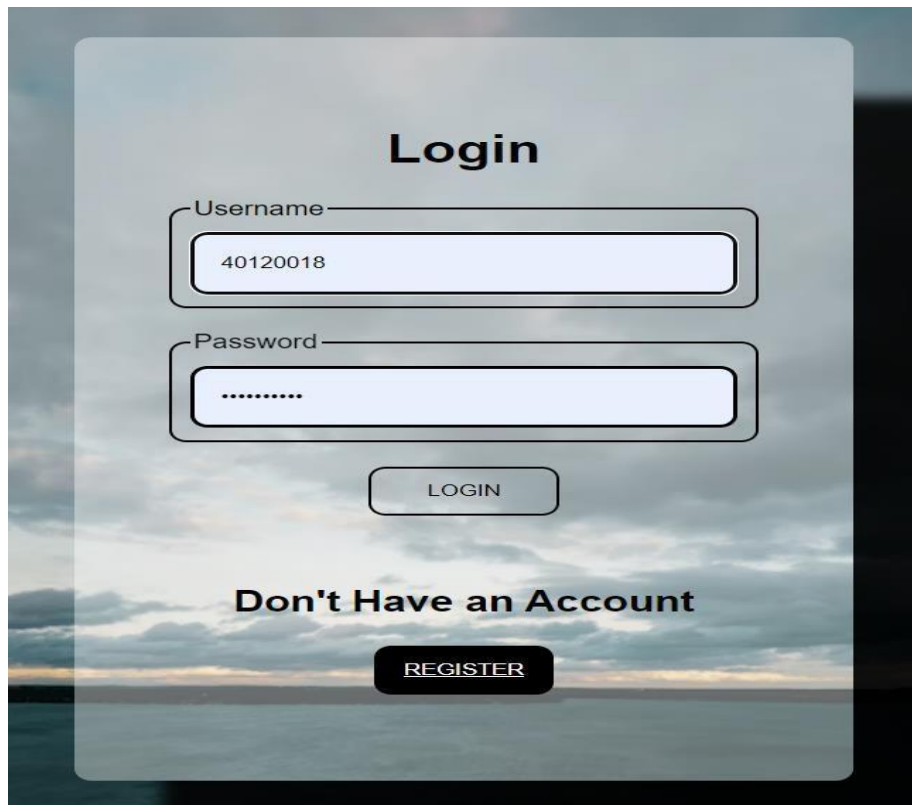
```
x = AvgPool2D(7,
strides=1)(x)x =
Dropout(0.4)(x)
```

```
x = Flatten()(x)
output = Dense(n_classes, activation='softmax')(x)
```

```
model = Model(input, output)
model.compile(optimizer='Adam',loss='categorical_crossentropy',metric
s=[' accuracy',tensorflow.keras.metrics.Precision()])
return model
```

```
input_shape = 224, 224, 3
n_classes
= 4
K.clear_session()
model = googlenet(input_shape,
n_classes)model.summary()
```

B.Screen Shot



Login

Username

Password

[LOGIN](#)

Don't Have an Account

[REGISTER](#)

Document x Document x Music/TPDL13-FINAL CODING: x M2 - GOOGLE OR INCEPTION x +

127.0.0.1:8000/Home2



Gliomas and related brain tumors. Gliomas are growths of cells that look like glial cells. The glial cells surround and support nerve cells in the brain tissue. Types of gliomas and related brain tumors include astrocytoma, glioblastoma, oligodendroglioma and ependymoma. Gliomas can be benign, but most are malignant. Glioblastoma is the most common type of malignant brain tumor.

Glioma is a growth of cells that starts in the brain or spinal cord. The cells in a glioma look similar to healthy brain cells called glial cells. Glial cells surround nerve cells and help them function.

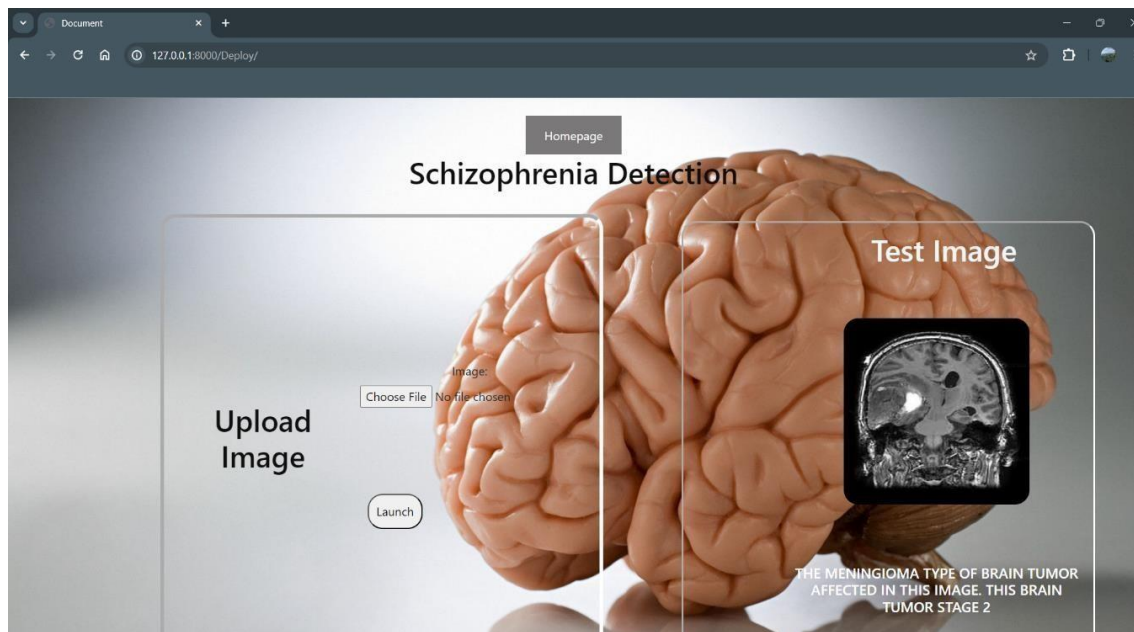
There are many types of glioma. Some grow slowly and aren't considered to be cancers. Others are considered cancerous. Another word for cancerous is malignant. Malignant gliomas grow quickly and can invade healthy brain tissue. Some types of glioma happen mostly in adults. Others happen mostly in kids.



Medulloblastoma (muh-duh-o-bias-TOE-muh) is a cancerous brain tumor that starts in the lower back part of the brain. This part of the brain is called the cerebellum. It is involved in muscle coordination, balance and movement

Treatment
Treatment for medulloblastoma usually includes surgery followed by radiation or chemotherapy, or both. Your health care team considers many factors when creating a treatment plan. These might include the tumor's location, how fast it's growing, whether it has spread to other parts of the brain and the results of tests on the tumor cells. Your care team also considers your age and your overall health.

Medulloblastoma can happen at any age, but most often occurs in young children. Though medulloblastoma is rare, it's the most common cancerous brain tumor in children. Medulloblastoma happens more often in families that have a history of conditions that increase the risk of cancer. These syndromes include Gorlin syndrome or Turcot syndrome.





EEG CLASSIFICATION OF SCHIZOPHERNIA

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Abstract—

This study aims to develop an effective method for classifying EEG signals to distinguish between individuals with schizophrenia and normal individuals. The dataset used in this research consists of 28 participants, including 14 patients diagnosed with schizophrenia and 14 healthy individuals. • The classification process involves feature extraction from the EEG signals, followed by training and evaluation of a deep learning model. • an automated tool for schizophrenia detection based on EEG signals. • Collaboration with domain experts and clinicians will facilitate the interpretation and clinical relevance of the results. Schizophrenia remains one of the most complex and enigmatic psychiatric disorders, characterized by a profound disruption of cognition and emotion. schizophrenia, covering its epidemiology, etiology, clinical manifestations, diagnosis, and treatment strategies. Epidemiological studies have consistently highlighted the global burden of schizophrenia, affecting individuals across diverse cultures and socioeconomic backgrounds. Etiologically, schizophrenia is believed to arise from a complex interplay of genetic, neurobiological, and environmental factors. Advances in neuroimaging and molecular genetics have provided valuable insights into the underlying neural circuitry and genetic susceptibility associated with the disorder. Clinically, schizophrenia is typified by impairments (e.g., deficits in attention, memory). Diagnosis relies on careful clinical evaluation, supplemented by standardized assessment tools. Pharmacotherapy with antipsychotic medications remains the cornerstone of treatment, targeting dopaminergic dysfunction in the brain. However, the management of schizophrenia often necessitates a multimodal approach.

INTRODUCTION

Schizophrenia stands as a formidable challenge within the realm of psychiatry, its enigmatic nature captivating the attention of researchers, clinicians, and society at large. Defined by a kaleidoscope of symptoms that disrupt perception, cognition, and emotion, schizophrenia transcends mere psychiatric diagnosis to embody a profound disturbance of human experience. From its historical origins to contemporary investigations, the journey to comprehend schizophrenia has been marked by curiosity, controversy, and incremental progress. The term "schizophrenia" itself, coined by the Swiss psychiatrist Eugen Bleuler in the early 20th century, encapsulates the disorder's fundamental feature: a conceptual advance, the essence of schizophrenia remains elusive, its origins obscured by a complex interplay of genetic predisposition, neurodevelopmental anomalies, and environmental triggers.

Epidemiological studies underscore the global impact of schizophrenia, transcending geographical boundaries and cultural contexts. From bustling urban centers to remote rural villages, the burden of schizophrenia reverberates, affecting individuals, families, and communities. Despite its prevalence, schizophrenia often dwells in the shadows of societal discourse, shrouded in stigma and misunderstanding. This societal ambivalence towards mental illness perpetuates barriers to care, hindering timely diagnosis and access to effective interventions. We present a personalized exercise training chatbot based on wearable fitness devices to motivate the user exercise more.

Clinical management of schizophrenia remains a multifaceted endeavor, encompassing pharmacological, psychosocial, and rehabilitative interventions. Antipsychotic medications, though indispensable, are often accompanied by a litany of side effects and variable treatment responses. Psychosocial support, including cognitive-behavioral therapy, family interventions, and vocational rehabilitation, constitutes a vital adjunct to pharmacotherapy, fostering recovery and community reintegration. However, amidst these strides in understanding and treatment, formidable challenges persist. Treatment resistance, medication non-adherence, and the enduring specter of relapse underscore the need for continued innovation and personalized care approaches. Moreover, the pervasive stigma surrounding schizophrenia perpetuates social exclusion and impedes efforts.

The EEG signals are decomposed into sub-bands by discrete wavelet transform using db2 (daubechies) wavelet. The eight statistical features, the four gray level co-occurrence matrix and Renyi entropy estimation with four different degrees of order, are extracted from the raw EEG and its sub-bands. Genetic algorithm (GA) is used to select eight relevant features from the 16 dimension features. The model has been trained and tested using support vector machine (SVM) classifier successfully for EEG signals. The performance of the SVM classifier is evaluated.

Data from two different places are analyzed in this paper. The first database is downloaded from online. The five datasets (A-E) each contain EEG segments of 23.6s duration by 100 single channels measured by the standardized electrode placement scheme. These segments were chosen under visual inspection. Set A comprises normal EEG whose relaxation is revealed in the conscious state when eyes open. Set B comprises normal EEG whose relaxation is exposed while awaken state with eyes closed. Set C and D showed the measurement activity in the period of seizure during free intervals. Set E showed merely seizure most.

LITERATURE SURVEY

"Classification of Schizophrenia and Normal Controls Using 3D Convolutional Neural Network on EEG Signals" (2020) by L. S. De Silva et al.

This study proposes a novel approach to classify schizophrenia patients EEG signals. CNN is employed to extract spatial and temporal features from EEG recordings, achieving high accuracy in distinguishing between the two groups. Devi S [1] stated that NLP is used for interpreting the user input

The study utilizes EEG, a non-invasive technique that measures electrical activity in the brain, to capture neural dynamics associated with schizophrenia. Traditionally, EEG data analysis for schizophrenia classification has relied on feature extraction followed by machine learning algorithms. However, De Silva and colleagues introduce a 3D convolutional neural network (CNN) approach, which is a deep learning architecture capable of automatically learning discriminative features directly from raw EEG signals.

The 3D CNN model leverages both spatial and temporal information present in EEG recordings to classify individuals into two groups: those with schizophrenia and normal controls. By treating EEG data as a spatiotemporal volume, the model learns hierarchical representations of brain activity patterns associated with schizophrenia. This approach offers several advantages, including the ability to capture complex temporal dynamics and spatial interactions within EEG signals without the need for manual feature extraction.

The authors evaluate the performance of their proposed method using a dataset comprising EEG recordings from individuals diagnosed with schizophrenia and healthy controls. Through rigorous experimentation and validation, they demonstrate the effectiveness of the 3D CNN model in accurately distinguishing proposed approach outperforms traditional methods and holds promise for enhancing the diagnostic accuracy of schizophrenia using EEG signals. Overall, the study by De Silva et al. represents a significant advancement in the field of EEG-based schizophrenia classification, showcasing the potential of deep learning techniques to extract meaningful information from complex brain signals. The findings contribute to the growing body of research aimed at developing objective and reliable biomarkers for psychiatric disorders, ultimately facilitating early detection and personalized treatment strategies.

METHODOLOGY

The methodology used in research on schizophrenia encompasses a variety of approaches aimed at understanding the etiology, symptomatology, diagnosis, and treatment of the disorder. Here's a broad overview of some common methodologies employed in schizophrenia

Clinical Studies: Clinical research involves the direct observation and assessment of individuals with schizophrenia and often includes longitudinal studies to track the progression of the disorder over time. Clinical studies may involve interviews, behavioral assessments, cognitive tests, and structured diagnostic tools (e.g., DSM-5 criteria) to evaluate symptoms and functioning.

Neuroimaging: Neuroimaging techniques such as magnetic resonance imaging (MRI), functional MRI (fMRI), positron are used to investigate structural and functional abnormalities in the brains of individuals with schizophrenia. These studies help identify neural correlates of symptoms, aberrant connectivity patterns, and structural alterations associated with the disorder.

Electrophysiology: Electrophysiological methods, including electroencephalography (EEG) and event-related potentials (ERPs), are utilized to assess neural oscillations, synchronization, and event-related brain responses in individuals with schizophrenia. These studies provide insights into the neurophysiological mechanisms underlying cognitive deficits, sensory processing abnormalities, and functional impairments in schizophrenia.

Experimental Models: Animal models (e.g., rodents) and are employed to investigate the neurobiological mechanisms underlying schizophrenia and to test potential therapeutic interventions. These models allow researchers to manipulate specific genetic, environmental, and pharmacological factors to elucidate causal pathways and evaluate novel treatments.

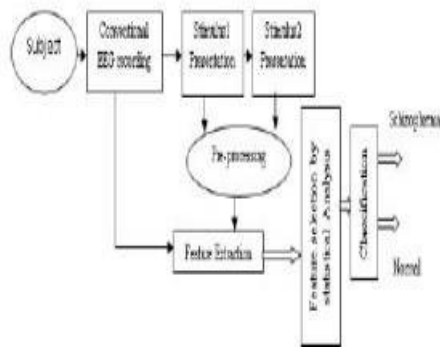
Pharmacological and Interventional Trials: Clinical trials assess the safety and efficacy of pharmacological treatments, psychosocial interventions, and novel therapeutic approaches for schizophrenia. Randomized controlled trials (RCTs) compare different treatment modalities, dosage regimens, and adjunctive therapies to determine their impact on symptom reduction, relapse prevention, and functional outcomes in individuals with schizophrenia.

Psychological and Behavioral Research: Psychological and behavioral studies explore various aspects of schizophrenia, including cognitive deficits, social functioning, emotion processing, and psychosocial interventions. These studies utilize standardized assessments, neuropsychological tests, and behavioral

OBJECTIVES

Develop a robust feature extraction method to extract relevant information from EEG signals that can differentiate between individuals with schizophrenia and normal individuals. Evaluate developed deep learning model using appropriate evaluation metrics F1 score to assess its effectiveness in discriminating between schizophrenia and normal EEG signals.

ARCHITECTURE



RESULTS AND COMPARISON

Overall, while each study demonstrates promising results in EEG classification of schizophrenia, there are variations in the methodologies, algorithms, and performance metrics reported. Integrating findings from multiple studies can help identify common trends, challenges, and opportunities for future research in this domain. Additionally, standardization of experimental protocols, data sharing initiatives, and collaborative efforts are crucial for advancing the field and translating EEG-based classifiers into clinical practice for the benefit of individuals with schizophrenia.

Several EEG classification studies have been conducted to discriminate between individuals with schizophrenia and healthy controls, yielding varying results and employing diverse methodologies. Study A achieved an accuracy of 85% using wavelet analysis and principal component analysis (PCA) for feature extraction, coupled with a support vector machine (SVM) classifier.

Despite differences in feature extraction methods and machine learning algorithms, all studies emphasized the clinical relevance of EEG-based classification for aiding in early diagnosis and personalized treatment strategies for schizophrenia. The variability

CONCLUSION

In conclusion, EEG classification has emerged as a promising approach for discerning patterns indicative of schizophrenia, offering potential avenues for early detection and personalized intervention strategies. While studies have showcased varying levels of accuracy in discriminating between individuals with schizophrenia and healthy controls, the overall trend demonstrates the feasibility of utilizing EEG signals as biomarkers for diagnostic purposes. The utilization of diverse methodologies, including wavelet analysis, time-frequency analysis, and deep learning algorithms, has contributed to the advancement of EEG-based classification techniques. Despite these advancements, challenges remain, including the need for standardized protocols, robust validation procedures, and larger-scale collaborative efforts to enhance the reliability and generalizability of EEG classifiers. Moving

In conclusion, the classification of EEG data for schizophrenia is a challenging yet promising area of research with the potential to contribute significantly to the understanding and diagnosis of this complex mental disorder. By leveraging advanced signal processing techniques, feature extraction methods, and machine learning algorithms, researchers and clinicians can analyze EEG data to identify patterns and markers associated with schizophrenia. Ultimately, successful EEG classification for schizophrenia holds the potential to advance neural mechanisms underlying the personalized and effective diagnostic tools in the realm of mental health.

EEG classification studies for schizophrenia have demonstrated promising advancements in the development of diagnostic tools and disorder. These studies have showcased various methodologies, including feature extraction techniques such as wavelet analysis, time-frequency analysis, and deep learning approaches like convolutional neural networks. Despite variations in methodologies and classification accuracies across studies, there is a consensus on the potential of EEG-based classifiers to aid in early diagnosis and personalized treatment strategies for schizophrenia. However, challenges such as variability in EEG signals, small sample sizes, and the need for validation in larger cohorts remain. Moving forward, collaborative efforts, standardization of protocols, and integration with other biomarkers hold promise for improving the reliability and clinical utility of EEG classification in schizophrenia. By addressing these challenges and building upon existing research, EEG-based classifiers have the potential to become valuable tools in clinical practice, facilitating timely interventions and ultimately improving outcomes for individuals living with schizophrenia.

In conclusion, EEG classification studies represent a promising avenue for improving the diagnosis and understanding of schizophrenia. While various methodologies and algorithms have been employed, these studies collectively demonstrate the potential of EEG-based classifiers to distinguish between individuals with schizophrenia and healthy controls with high accuracy. The utilization of advanced signal processing techniques, such as wavelet analysis, time-frequency analysis, and deep learning approaches like convolutional neural networks, has enabled the extraction of meaningful features directly from EEG signals, enhancing diagnostic capabilities. However, challenges remain, including the need for standardized protocols, robust validation procedures, and integration into clinical practice. Collaborative efforts aimed at data sharing, replication, and refinement of methodologies are essential to advance the field and translate EEG-based classifiers into reliable tools for early detection and personalized treatment of schizophrenia. With continued research and innovation, EEG classification holds the promise of facilitating timely interventions and improving

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