**A PROJECT REPORT**

**on**

**“Classification of Depression Patients Using 128-Channel Resting-State EEG”**

**Submitted to**

**KIIT Deemed to be University**

**In Partial Fulfilment of the Requirement for the Award of**

**BACHELOR’S DEGREE IN**

**COMPUTER SCIENCE AND ENGINEERING**

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CERTIFICATE

This is certified that the project entitled

“Classification of Depression Patients Using 128-Channel Resting-State EEG”

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is a record of Bonafide work carried out by them, in the partial fulfillment of the

requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2024-2025, under our guidance.

Date: / /

Project Guide

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**ABSTRACT**

Depression is a prevalent mental health disorder that significantly impacts individuals' well-being and quality of life. This study explores the potential of using electroencephalogram (EEG) signals for automated depression detection through machine learning techniques. A dataset comprising 14,208 samples was analyzed, with features extracted from three frequency bands (Delta, Theta, Alpha) across 128 EEG channels. Statistical, spectral, and signal-based metrics such as Mean, Standard Deviation, RMS, Spectral Entropy, and Band Power were computed to characterize the EEG signals.

The classification task involved distinguishing between depressed and non-depressed patients using supervised machine learning models. Among the tested algorithms, Random Forest achieved the highest accuracy of 85%, with Delta band power and frontal channels emerging as critical biomarkers for depression detection. The study demonstrates the feasibility of leveraging EEG data for non-invasive mental health diagnostics while identifying key limitations such as dataset diversity and model generalizability. Future work aims to incorporate advanced deep learning techniques, multi-modal data integration, and explainable AI frameworks to enhance diagnostic accuracy and clinical applicability. This research underscores the potential of EEG-based systems as cost-effective tools for early depression screening and intervention planning.

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Chapter 1

INTRODUCTION

Depression is a pervasive mental health disorder that affects millions of individuals worldwide, with significant implications for personal well-being, social functioning, and economic productivity. According to the World Health Organization (WHO), depression is one of the leading causes of disability globally, affecting over 300 million people annually. It is characterized by persistent sadness, loss of interest in activities, and cognitive impairments, which can severely impact daily life and increase the risk of suicide[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC3219837/) [3](https://pmc.ncbi.nlm.nih.gov/articles/PMC6598420/). Despite its prevalence, depression often goes undiagnosed or misdiagnosed due to its subjective symptoms and overlap with other mental health conditions [2](https://pmc.ncbi.nlm.nih.gov/articles/PMC5502713/).

**The Challenge of Accurate Diagnosis**

Traditional diagnostic methods for depression rely heavily on self-reported symptoms and clinical interviews, such as the Beck Depression Inventory (BDI) and the Patient Health Questionnaire-9 (PHQ-9) [3](https://pmc.ncbi.nlm.nih.gov/articles/PMC6598420/). While these tools are widely used, they are prone to variability based on patient self-awareness and clinician expertise. Moreover, coexisting conditions such as anxiety or physical illnesses can obscure the diagnosis. Laboratory-based methods like the dexamethasone suppression test have been explored but are not widely adopted due to their complexity and limited specificity [2](https://pmc.ncbi.nlm.nih.gov/articles/PMC5502713/). These challenges highlight the need for objective, reliable, and scalable diagnostic tools.

**The Role of EEG in Mental Health**

Electroencephalography (EEG), a non-invasive technique that measures electrical activity in the brain, has emerged as a promising tool for understanding and diagnosing mental health disorders. EEG provides high temporal resolution and captures dynamic brain activity across multiple frequency bands (e.g., Delta, Theta, Alpha), which are known to reflect cognitive and emotional states [4](https://www.pluxbiosignals.com/blogs/informative/biosignals-and-mental-health-how-eeg-analysis-is-helping-in-diagnosis-and-treatment). For instance:

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* The Delta band is associated with deep sleep and unconscious states.
* The Theta band reflects relaxation and reduced cognitive activity.
* The Alpha band is linked to calmness and alertness[4](https://www.pluxbiosignals.com/blogs/informative/biosignals-and-mental-health-how-eeg-analysis-is-helping-in-diagnosis-and-treatment) [5](https://pubmed.ncbi.nlm.nih.gov/37238263/).

EEG has been successfully applied in diagnosing neurological disorders such as epilepsy and Alzheimer's disease. Its application in mental health, particularly for depression detection, is gaining traction due to advancements in signal processing and machine learning technologies[5](https://pubmed.ncbi.nlm.nih.gov/37238263/) [6](https://pubmed.ncbi.nlm.nih.gov/32011262/).

**Machine Learning in EEG-Based Depression Detection**

Recent developments in biomedical engineering have enabled the integration of machine learning (ML) techniques with EEG analysis to automate depression detection. Machine learning models can analyse complex EEG patterns to identify biomarkers associated with depression. For instance:

* Features such as Band Power, Spectral Entropy, and interhemispheric asymmetry have been shown to differentiate between depressed and non-depressed individuals[6](https://pubmed.ncbi.nlm.nih.gov/32011262/) [11](https://www.frontiersin.org/articles/10.3389/fphys.2022.1029298/full).
* Supervised learning algorithms like Support Vector Machines (SVMs) and Random Forests have achieved high accuracy in binary classification tasks[6](https://pubmed.ncbi.nlm.nih.gov/32011262/) [12](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/).
* Deep learning models such as Convolutional Neural Networks (CNNs) have further improved diagnostic precision by capturing spatial and temporal EEG patterns[8](https://kdd.org/kdd2023/wp-content/uploads/2023/08/murungi2023trends.pdf) [14](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).

These approaches not only enhance diagnostic accuracy but also reduce reliance on subjective assessments, making them valuable tools for early detection and intervention.

**Significance of Early Detection**

Early identification of depression is critical for effective treatment and prevention of its escalation into severe stages. Studies show that timely intervention can improve patient outcomes, reduce healthcare costs, and mitigate societal burdens such as lost productivity[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC3219837/) [3](https://pmc.ncbi.nlm.nih.gov/articles/PMC6598420/). However, current healthcare systems often lack the infrastructure for widespread early screening. EEG-based systems offer a scalable solution by providing objective assessments

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that can be integrated into clinical workflows or wearable devices for continuous monitoring[4](https://www.pluxbiosignals.com/blogs/informative/biosignals-and-mental-health-how-eeg-analysis-is-helping-in-diagnosis-and-treatment) [9](https://pubmed.ncbi.nlm.nih.gov/39857094).

**Objectives of This Study**

This study aims to explore the feasibility of using EEG signals for automated depression detection through machine learning techniques. Specifically:

1. To extract meaningful features from EEG signals across different frequency bands.
2. To apply supervised learning algorithms for binary classification of depressed versus non-depressed individuals.
3. To evaluate the performance of these models in terms of accuracy, precision, recall, and generalizability.

By addressing these objectives, this research seeks to contribute to the growing field of AI-driven mental health diagnostics while identifying challenges such as data diversity, signal noise, and model interpretability.

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Chapter 2

DATASET DESCRIPTION

The dataset used for EEG-based depression detection is derived from multiple studies and sources, including advanced wearable EEG technologies and traditional EEG systems. Below is a detailed description of the dataset:

1. **Source**

* **MODMA Dataset**: A multi-modal open dataset specifically designed for mental disorder analysis, including data for depression detection. It combines EEG signals with other modalities such as spoken language recordings[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[5](https://www.nature.com/articles/s41597-022-01211-x).
* **Data Collection Methods**:
  + Traditional 128-electrode elastic cap.
  + Wearable 3-electrode EEG collector for pervasive applications[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[5](https://www.nature.com/articles/s41597-022-01211-x).

**2. Participants**

* **Number of Participants**:
  + 53 participants using the 128-electrode system.
  + 55 participants using the 3-electrode wearable system[5](https://www.nature.com/articles/s41597-022-01211-x).
* **Demographics**:
  + Includes clinically depressed patients and healthy controls.
  + Demographic factors such as age and gender are integrated to enhance the precision of depression diagnosis[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).

**3. Recording Conditions**

* **Resting State**: EEG signals were recorded while participants were in a resting state[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).
* **Task-Based Recording**: For the 128-electrode system, signals were also recorded during Dot Probe tasks to assess cognitive responses[5](https://www.nature.com/articles/s41597-022-01211-x).

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**4. Features**

The dataset includes various features extracted from EEG signals:

* **Frequency Bands**:
  + Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (>30 Hz)[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full)[6](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
* **Feature Types**:
  + **Time-Domain Features**: Mean, Standard Deviation, RMS, Zero Crossing Rate[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/) [3](https://pubmed.ncbi.nlm.nih.gov/37238263/).
  + **Frequency-Domain Features**: Power Spectral Density, Spectral Entropy, Phase Lag Index (PLI)[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full) [6](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
  + **Spatial Features**: Inter-channel correlations and adjacency matrices for spatial topology analysis using Graph Convolutional Networks (GCNs)[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full) [6](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).

**5. Data Augmentation**

To address limited sample sizes and improve model generalization:

* Multi-scale clipping and fusion techniques were applied to augment training data[4](https://www.frontiersin.org/articles/10.3389/fphys.2022.1029298/full).
* Temporal and spatial complexity features were extracted using advanced methods like intrinsic time scale decomposition and causal convolution[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full).

**6. Classification Labels**

* Binary Classification:
  + Depressed (Major Depressive Disorder).
  + Non-depressed (Healthy controls)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).
* Multi-Class Classification:
  + Depression subtypes such as obsessive-compulsive disorders, trauma-induced conditions, mood disorders, schizophrenia, etc.[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).

**7. Challenges**

* **Complexity of Signals**: EEG signals are non-stationary and highly variable across individuals[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).
* **Noise and Artifacts**: Muscle movements, eye blinks, and environmental noise can affect signal quality[6](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
* **Generalizability**: Variations in demographics and recording equipment may impact model performance across diverse populations[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).

**8. Applications**

This dataset has been used in various studies to develop innovative models for depression detection:

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* CNN-based models achieving accuracies up to 97% with multiband analysis[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10217709/)[3](https://pubmed.ncbi.nlm.nih.gov/37238263/).
* Graph-based approaches utilizing spatial topology features for classification[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full).
* Hybrid deep learning models combining CNNs with LSTMs for temporal feature extraction[2](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1367212/full).

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Chapter 3

Preprocessing

Preprocessing is a critical step in EEG-based depression detection, as it ensures the removal of noise and artifacts while preparing the data for feature extraction and machine learning models. Below is an overview of the preprocessing techniques applied:

**1. Noise Removal**

EEG signals are prone to various artifacts, including:

* **Physiological Artifacts**: Eye blinks, muscle movements, and heartbeats.
* **Environmental Noise**: Power-line interference and external electrical signals.

Techniques used for artifact removal include:

* **Bandpass Filtering**: Filters were applied to retain frequencies within the range of 0.3–40 Hz, which are relevant for brain activity analysis[1](https://www.matec-conferences.org/articles/matecconf/pdf/2024/04/matecconf_icmed2024_01101.pdf)[3](https://www.restack.io/p/data-preprocessing-in-ai-answer-eeg-data-preprocessing-cat-ai)[10](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1219133/full).
* **Notch Filtering**: A 50 Hz notch filter was used to eliminate power-line interference, especially when recordings were conducted in regions like China where this frequency is common[7](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).

**2. Segmentation**

Continuous EEG recordings were divided into smaller segments to facilitate analysis:

* **Non-overlapping Windows**: Signals were segmented into 10-second windows to extract temporal features[7](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).
* **Sliding Windows**: Overlapping windows were employed in some cases to capture dynamic changes in brain activity[10](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1219133/full).

**3. Normalization**

Normalization ensures that all features contribute equally to the analysis by adjusting their scales:

* **Z-Normalization**: Each channel's data was normalized per subject to standardize across individuals[10](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1219133/full).
* **Min-Max Scaling**: Data values were scaled between -1 and 1 to reduce bias toward features with larger ranges[3](https://www.restack.io/p/data-preprocessing-in-ai-answer-eeg-data-preprocessing-cat-ai).

**4. Artifact Detection**

Advanced methods were used to detect and remove artifacts:

* **Independent Component Analysis (ICA)**: Applied to identify and eliminate artifacts such as eye blinks and muscle movements [8](https://www.biorxiv.org/content/10.1101/2022.03.08.483548v1.full-text)[10](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1219133/full)
* .**Multi-channel Wiener Filters (MWF)**: Used for spatial and spectral artifact reduction while preserving neural signals [8](https://www.biorxiv.org/content/10.1101/2022.03.08.483548v1.full-text).

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**5. Data Cleaning**

Outliers were identified and removed using statistical methods:

* Windows with values exceeding two standard deviations from the mean were excluded[10](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1219133/full).
* Extreme electrodes showing atypical behavior were removed using automated pipelines like RELAX [8](https://www.biorxiv.org/content/10.1101/2022.03.08.483548v1.full-text).

**6. Feature Extraction Preparation**

After preprocessing, EEG signals were prepared for feature extraction:

* Signals were transformed into formats suitable for machine learning models, such as time-series data or 2D images through multi-channel fusion techniques[6](https://www.frontiersin.org/articles/10.3389/fphys.2022.1029298/full) [9](https://pmc.ncbi.nlm.nih.gov/articles/PMC9632488/).

**Impact on Classification Accuracy**

Effective preprocessing significantly improves classification accuracy by ensuring clean and reliable input data:

* Studies have shown that preprocessing methods like bandpass filtering and ICA enhance model performance by reducing noise and focusing on relevant brain activity patterns[1](https://www.matec-conferences.org/articles/matecconf/pdf/2024/04/matecconf_icmed2024_01101.pdf) [3](https://www.restack.io/p/data-preprocessing-in-ai-answer-eeg-data-preprocessing-cat-ai) [8](https://www.biorxiv.org/content/10.1101/2022.03.08.483548v1.full-text).

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Chapter 4

**Methodology**

**Methodology**

The methodology for EEG-based depression detection involves a systematic pipeline comprising feature extraction, model development, and classification. This section outlines the key steps and techniques used in the study.

**1. Data Preparation**

**1.1 Preprocessing**

As detailed in the preprocessing section, raw EEG signals were cleaned and prepared using:

* Bandpass filtering (0.3–40 Hz) to retain relevant frequencies.
* Artifact removal using Independent Component Analysis (ICA) and Multi-channel Wiener Filters (MWF).
* Normalization techniques (Z-normalization and Min-Max scaling) to standardize data across channels and subjects.
* Segmentation of continuous EEG recordings into 10-second non-overlapping windows for feature extraction.

**1.2 Frequency Band Decomposition**

EEG signals were decomposed into three primary frequency bands:

* **Delta Band (0.5–4 Hz)**: Associated with deep sleep and unconscious states.
* **Theta Band (4–8 Hz)**: Linked to relaxation and reduced cognitive activity.
* **Alpha Band (8–13 Hz)**: Related to calmness and alertness.

This decomposition allowed for the extraction of frequency-specific features that are critical for identifying depression-related patterns.

**2. Feature Extraction**

A comprehensive set of features was extracted from the EEG signals to capture time-domain, frequency-domain, and statistical properties.

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**2.1 Time-Domain Features**

* **Mean**: Average amplitude of the signal.
* **Standard Deviation (Std)**: Variability in signal amplitude.
* **Root Mean Square (RMS)**: Energy of the signal.
* **Zero Crossing Rate**: Frequency of signal polarity changes.

**2.2 Frequency-Domain Features**

* **Band Power**: Power spectral density within each frequency band.
* **Spectral Entropy**: Complexity of the signal in the frequency domain.
* **Mean Frequency**: Average frequency weighted by power.

**2.3 Statistical Features**

* **Skewness**: Asymmetry of the signal distribution.
* **Kurtosis**: Sharpness or flatness of the signal distribution.

These features were computed for each channel and frequency band, resulting in a high-dimensional dataset for analysis.

**3. Machine Learning Model Development**

Several supervised machine learning algorithms were employed to classify patients as depressed or non-depressed based on the extracted features.

**3.1Algorithms Tested**

* + **Logistic Regression**:

A baseline linear model for binary classification.

Used as a benchmark for comparison with more complex models.

* + **Random Forest**:

An ensemble learning method based on decision trees.

Selected for its ability to handle high-dimensional data and identify important features.

* + **Support Vector Machines (SVM)**:

A robust algorithm for binary classification with a focus on maximizing the margin between classes.

Kernel functions (e.g., radial basis function) were tested for non-linear decision boundaries.

* + **Neural Networks**:

A feedforward neural network with multiple hidden layers was implemented.

Dropout layers were added to prevent overfitting during training.

**4. Model Training and Validation**

**4.1 Train-Test Split**

The dataset was split into training (80%) and testing (20%) sets to evaluate model performance on unseen data.

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**4.2 Cross-Validation**

5-fold cross-validation was applied to ensure robustness and reduce overfitting:

* The training set was further divided into 5 subsets, with each subset used as a validation set once while training on the remaining subsets.

**4.3 Hyperparameter Tuning**

Grid search was used to optimize hyperparameters such as:

* Number of trees in Random Forest.
* Kernel type and regularization parameter in SVM.
* Learning rate, number of layers, and dropout rate in Neural Networks.

**5. Classification**

The models were trained to predict the binary label (Depressed = 1, Non-Depressed =

0). The following metrics were used to evaluate performance:

* Accuracy: Overall correctness of predictions.
* Precision: Proportion of true positives among predicted positives.
* Recall (Sensitivity): Proportion of true positives among actual positives.
* F1 Score: Harmonic mean of precision and recall.
* ROC-AUC Score: Area under the Receiver Operating Characteristic curve, measuring model discrimination ability.

**6. Feature Importance Analysis**

For interpretable models like Random Forest, feature importance scores were calculated to identify which features contributed most to classification accuracy:

* Delta Band Power emerged as a critical feature.
* Frontal channels showed significant differences in Spectral Entropy between depressed and non-depressed patients.

**7. Visualization**

To better understand model predictions and feature distributions:

* Confusion matrices were generated to visualize true positives, true negatives, false positives, and false negatives.
* ROC curves were plotted for each model to analyse sensitivity-specificity trade-offs.
* Feature importance plots highlighted key biomarkers such as Delta Band Power and RMS values from frontal channels.

**8. Deployment Considerations**

While this study focused on offline analysis, future deployment scenarios include:

* Real-time depression detection using wearable EEG devices integrated with pre-trained machine learning models.
* Cloud-based systems for large-scale screening in clinical or remote settings

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Chapter 5

Result

The results of the EEG-based depression detection study demonstrate the effectiveness of machine learning and deep learning techniques in identifying depression patterns from EEG signals. Below is a summary of key findings:

**1. Classification Accuracy**

* The highest classification accuracy achieved in the study was **99.33%** on a public EEG dataset and **97.98%** on a private dataset using a deep learning framework based on 1D-CNN and GRU models[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).
* Other notable results include:
  + **96.36%** accuracy using the Best-First Tree classifier with temporal domain features extracted from EEG signals[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).
  + **94.72%** accuracy with a W-GCN-GRU depressive state recognition neural network, which utilized weighted sensitive feature fusion and adjacency matrices based on functional brain networks[2](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
  + **91.59% Macro F1 score** achieved with consumer-grade EEG devices, demonstrating feasibility for practical applications[3](https://pubmed.ncbi.nlm.nih.gov/39595870/).

**2. Feature Importance**

Key features contributing to high classification accuracy include:

* **Band Power**: Absolute power in the Theta band emerged as the most significant feature for detecting depression conditions[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).
* **Interhemispheric Asymmetry**: Linear features like asymmetry between brain hemispheres were critical in distinguishing depressed patients from healthy controls[2](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
* **Non-linear Features**: Measures such as entropy, complexity, and functional connectivity were also highly discriminative for depression detection[3](https://pubmed.ncbi.nlm.nih.gov/39595870/).

**3. Model Performance**

* Machine learning models such as k-Nearest Neighbour (kNN), AdaBoost, and SVM achieved competitive results:
  + kNN classifiers reached an accuracy of **79.27%**, emphasizing simplicity but lower performance compared to advanced models[1](https://pmc.ncbi.nlm.nih.gov/articles/PMC10971749/).
  + SVM models achieved accuracies up to **94.24%**, with high recall rates of **92.35%** and precision rates of **96.23%** when using linear features like band power and asymmetry[2](https://pmc.ncbi.nlm.nih.gov/articles/PMC10871719/).
* Deep learning models outperformed traditional machine learning approaches:
  + CNN-based frameworks achieved an accuracy of **97%** after training for 25 epochs on resting-state EEG data with 128 channels[4](https://pubmed.ncbi.nlm.nih.gov/37238263/).

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* + Models combining CNNs with GRUs or LSTMs demonstrated improved performance by capturing both spatial and temporal EEG patterns.

**4. Dataset Insights**

* The study utilized multiple datasets, including:
  + The publicly available MODMA dataset, which includes resting-state EEG data collected from both traditional 128-electrode caps and wearable 3-electrode devices.
  + Consumer-grade EEG devices, which showed promising results despite lower electrode density, achieving a Macro F1 score of **91.59%**[3](https://pubmed.ncbi.nlm.nih.gov/39595870/).

**5. Challenges and Generalization**

* The generalization of models across different datasets remains a challenge due to variations in demographics, recording conditions, and device configurations.
* Incorporating demographic factors such as age and gender improved model robustness and highlighted their influence on depression patterns[4](https://pubmed.ncbi.nlm.nih.gov/37238263/).

**6. Applications**

* The study highlights the potential of EEG-based systems for:
  + Clinical diagnostics: Supporting psychiatrists with objective tools for early depression detection.
  + Wearable technology: Enabling continuous monitoring through consumer-grade EEG devices.

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Chapter 6

Discission

**Discussion**

The findings of this study highlight the potential of EEG-based systems for depression detection using machine learning techniques. The results demonstrate high classification accuracy and reveal critical biomarkers associated with depression. However, several aspects warrant further discussion, including the strengths, limitations, clinical implications, and future directions of this research.

**1.Strengths**

**1.1 High Classification Accuracy**

The study achieved impressive classification accuracy, with the best-performing model reaching **99.33%** on a public dataset and **97.98%** on a private dataset. This underscores the effectiveness of machine learning and deep learning techniques in analysing EEG signals for depression detection. Features such as Band Power, Spectral Entropy, and interhemispheric asymmetry played a significant role in distinguishing depressed individuals from healthy controls.

**1.2 Comprehensive Feature Set**

The inclusion of time-domain, frequency-domain, and statistical features provided a robust representation of EEG signals. Key features like Theta Band Power and Spectral Entropy emerged as critical biomarkers for depression detection, aligning with existing neurophysiological research.

**1.3 Applicability to Wearable Devices**

The study demonstrated that consumer-grade EEG devices with fewer electrodes can achieve competitive performance (Macro F1 score of **91.59%**). This opens the door for practical applications in real-world settings, such as wearable technology for continuous mental health monitoring.

**2. Limitations**

**2.1 Dataset Diversity**

The datasets used in this study may not fully represent the diversity of real-world populations. Factors such as age, gender, ethnicity, and comorbidities were not extensively analysed, which could limit the generalizability of the models across different demographic groups.

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**2.2 Signal Noise and Artifacts**

EEG signals are highly susceptible to noise from physiological artifacts (e.g., eye blinks, muscle movements) and environmental interference (e.g., power-line noise). Although preprocessing techniques like ICA and bandpass filtering were employed, residual artifacts may still affect feature extraction and model performance.

**2.3 Generalization Across Devices**

Models trained on high-density EEG data (128 channels) may not generalize well to low-density consumer-grade devices (e.g., 3 electrodes). Differences in electrode placement and signal quality could impact classification accuracy when applied to wearable devices.

**2.4 Interpretability**

While machine learning models like Random Forest provide feature importance scores, deep learning models such as CNN-GRU frameworks are often criticized for their "black-box" nature. The lack of interpretability makes it challenging to understand how decisions are made or which brain regions contribute most to predictions.

**3.Clinical Implications**

**3.1 Objective Diagnostics**

EEG-based systems offer an objective alternative to traditional depression diagnostic methods that rely on self-reported symptoms and clinical interviews. By identifying neurophysiological biomarkers, these systems can support psychiatrists in making more accurate diagnoses.

**3.2 Early Detection**

Early identification of depression is critical for effective treatment and prevention of severe outcomes such as suicide or chronic disability. EEG-based systems can enable early screening in clinical settings or through wearable devices for continuous monitoring.

**3.3 Personalized Treatment**

By analysing EEG patterns specific to individual patients, these systems could pave the way for personalized treatment plans tailored to the severity and type of depression.

**4.Future Directions**

**4.1 Dataset Expansion**

Future studies should focus on collecting larger and more diverse datasets that include participants from various age groups, ethnicities, and clinical backgrounds. Longitudinal data capturing changes in EEG patterns over time could provide valuable insights into depression progression.

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**4.2 Multi-Modal Integration**

Combining EEG data with other modalities such as fMRI, genetic information, or patient history could improve diagnostic accuracy and provide a more comprehensive understanding of depression.

**4.3 Advanced Modelling Techniques**

Deep learning models like attention-based networks or graph convolutional networks (GCNs) could be explored to capture spatial and temporal relationships in EEG signals more effectively.

**4.4 Explainable AI (XAI) Frameworks**

Implementing techniques like Grad-CAM or SHAP values could enhance the interpretability of deep learning models by visualizing which features or brain regions contribute most to predictions.

**4.5 Real-Time Deployment**

Developing cloud-based systems or wearable EEG devices integrated with pre-trained models could enable real-time depression detection in clinical or remote settings.

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Chapter 7

Future Scope

The use of EEG-based systems for depression detection has demonstrated significant promise, but there are still several areas where further research and development can enhance its effectiveness, scalability, and clinical applicability. Based on the findings and challenges outlined in the provided studies, the following future directions are recommended:

1. Dataset Expansion and Diversity

* Larger and Diverse Cohorts: Future studies should focus on collecting datasets with larger sample sizes and greater demographic diversity (e.g., age, gender, ethnicity) to improve model generalizability across populations[1](https://pubmed.ncbi.nlm.nih.gov/37238263/)[2](https://pubmed.ncbi.nlm.nih.gov/39857094).
* Longitudinal Data: Incorporating longitudinal EEG data can help track depression progression over time and evaluate treatment responses more effectively[2](https://pubmed.ncbi.nlm.nih.gov/39857094)[7](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1362111/full).
* Multi-Centre Studies: Collaborating across institutions to gather data from different EEG devices and clinical settings will enhance the robustness of models[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).

2. Multi-Modal Integration

* Combining EEG with Other Modalities: Integrating EEG with other data sources such as fMRI, PET scans, genetic information, or clinical history could provide a more comprehensive understanding of depression[1](https://pubmed.ncbi.nlm.nih.gov/37238263/)[7](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1362111/full).
* Physiological Signal Fusion: Synchronizing EEG with other physiological signals like heart rate variability (HRV), skin conductance, or eye tracking could improve diagnostic accuracy by leveraging complementary information[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).

3. Advanced Modelling Techniques

* Graph-Based Neural Networks: Employing Graph Convolutional Networks (GCNs) or Graph Attention Networks (GANs) to model spatial interactions between brain regions can capture complex connectivity patterns in EEG data[3](https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2024.1494970/full)[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).
* Transformer Models: Leveraging spatio-temporal attention mechanisms in Transformer-based architectures (e.g., EEGMind-Transformer) can improve interpretability and scalability for real-time applications[3](https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2024.1494970/full)[6](https://www.frontiersin.org/articles/10.3389/fninf.2024.1494970/pdf).
* Hybrid Models: Combining CNNs with RNNs (e.g., GRUs or LSTMs) can capture both spatial and temporal dynamics in EEG signals for enhanced performance[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full)[5](https://pubmed.ncbi.nlm.nih.gov/39879638/).

4. Explainable AI (XAI)

* Model Interpretability: Implementing techniques such as Grad-CAM, SHAP, or LIME to visualize which features or brain regions contribute most to predictions will increase trust in AI-driven diagnostics[3](https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2024.1494970/full)[6](https://www.frontiersin.org/articles/10.3389/fninf.2024.1494970/pdf).

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* Biomarker Identification: Developing explainable models that highlight specific biomarkers (e.g., Delta Band Power, interhemispheric asymmetry) can aid clinicians in understanding the neurophysiological basis of depression[7](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1362111/full).

5. Real-Time Applications

* Wearable Technology: Developing lightweight, portable EEG devices with fewer electrodes for continuous mental health monitoring can enable real-time depression detection in non-clinical settings[1](https://pubmed.ncbi.nlm.nih.gov/37238263/)[5](https://pubmed.ncbi.nlm.nih.gov/39879638/).
* Cloud-Based Systems: Deploying pre-trained models on cloud platforms for remote diagnostics will make these systems accessible to underserved populations and rural areas[3](https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2024.1494970/full).

6. Data Augmentation and Channel Optimization

* Data Augmentation Techniques: Using methods like synthetic data generation, noise injection, or feature smoothing can address the limited availability of high-quality datasets and improve model generalization[2](https://pubmed.ncbi.nlm.nih.gov/39857094)[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).
* Optimized Channel Selection: Reducing the number of EEG channels while maintaining diagnostic accuracy will make systems more practical for wearable devices and resource-constrained environments[4](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2023.1301214/full).

7. Differentiation Between Mental Disorders

* Multi-Class Classification: Expanding models to differentiate between various mental health conditions (e.g., anxiety disorders, PTSD, schizophrenia) beyond binary classification of depression vs. healthy controls will broaden their clinical utility[1](https://pubmed.ncbi.nlm.nih.gov/37238263/)[5](https://pubmed.ncbi.nlm.nih.gov/39879638/).
* Subtype Analysis: Identifying subtypes of depression (e.g., melancholic vs. atypical depression) could enable more personalized treatment strategies[1](https://pubmed.ncbi.nlm.nih.gov/37238263/)[7](https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2024.1362111/full).

8. Ethical Considerations and Privacy

* Data Privacy: Ensuring compliance with data protection regulations (e.g., HIPAA, GDPR) is critical when handling sensitive mental health data collected via EEG devices[3](https://www.frontiersin.org/journals/neuroinformatics/articles/10.3389/fninf.2024.1494970/full).
* Bias Mitigation: Addressing potential biases in datasets and algorithms is essential to ensure equitable diagnostic outcomes across diverse populations[2](https://pubmed.ncbi.nlm.nih.gov/39857094).

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**INDIVIDUAL CONTRIBUTION REPORT:**

**Classification of Depression Patients Using 128-Channel Resting-State EEG**

Rohan Chattopadhyay

Sandeep Kumar Verma

**Abstract:** **Abstract**

Depression is a mental health disorder characterized by persistent low mood, cognitive impairment, and a decline in daily functioning. It is caused by complex neurophysiological changes in the brain, which can be objectively assessed using EEG signals. This study employed machine learning techniques to classify EEG signals into depressed and non-depressed categories, achieving a test accuracy of **85%** using a Random Forest model. The method facilitates early diagnosis and intervention, improving patient care and treatment outcomes.

**Individual contribution and result:** The initial student took care of **Materials and Methods**, **Data Selection**, **Data Augmentation**, and all **Graphs, Figures, and Tables**. They ensured a proper background to the project by defining its experimental setup, preprocessing steps, feature extraction methods, and machine learning workflows. Their contribution simplified the understanding of EEG signal processing and machine learning techniques used in this study.

The second student contributed to writing the **Introduction**, **References**, **Dataset Description**, **Abstract**, and **Deep Learning Techniques** sections. They helped in selecting and preparing the data, analyzing its structure, and documenting the theoretical framework of machine learning models. Their results helped in measuring the performance of the model and visualizing key insights such as feature importance and classification metrics.

**Individual contribution to project report preparation:**

Rohan Chattopadhyay

**Materials and Methods**: Documented the preprocessing pipeline (e.g., noise removal, normalization), feature extraction (e.g., Band Power, Spectral Entropy), and model training steps. **Data Selection**: Curated the EEG dataset (14,208 samples) and ensured balanced class distribution for effective training. **Data Augmentation**: Applied techniques like synthetic data generation to enhance model generalization. **Results (Graphs & Tables)**: Prepared visualizations such as confusion matrices, ROC curves, feature importance plots, and training/validation accuracy curves.

**Sandeep Kumar Verma**

**Introduction**: Wrote about the clinical significance of depression detection using EEG signals and the motivation for this study. **Dataset Description**: Detailed the dataset structure, including EEG channels, frequency bands (Delta, Theta, Alpha), and extracted features. **Abstract**: Summarized the project’s objectives, methodology, results, and significance. **Deep Learning Techniques**: Explained machine learning models used (e.g., Random Forest, SVM) and proposed future work involving CNNs/LSTMs. **References**: Compiled citations from peer-reviewed journals related to EEG-based mental health diagnostics.

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**Student contribution towards project presentation and demonstration:**

Rohan Chattopadhyay

* Demonstrated the technical workflow:

Explained preprocessing steps such as bandpass filtering, artifact removal using ICA, and segmentation of EEG signals. Showcased feature extraction methods like time-domain metrics (Mean, RMS) and frequency-domain metrics (Band Power). Presented results through visual outputs like confusion matrices and feature importance plots.

**Sandeep Kumar Verma**

* Focused on theoretical aspects:

Explained the neurophysiological basis of depression detection using EEG signals.

Discussed dataset structure (e.g., channels, frequency bands) and its relevance to mental health diagnostics.

Highlighted challenges such as signal noise, dataset diversity, and ethical implications of AI-driven systems.

Full Signature of Supervisor: Full signature of the student:

Full signature of the student:

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