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Multi-Model Mental Disorder Detection

Under the Supervision of
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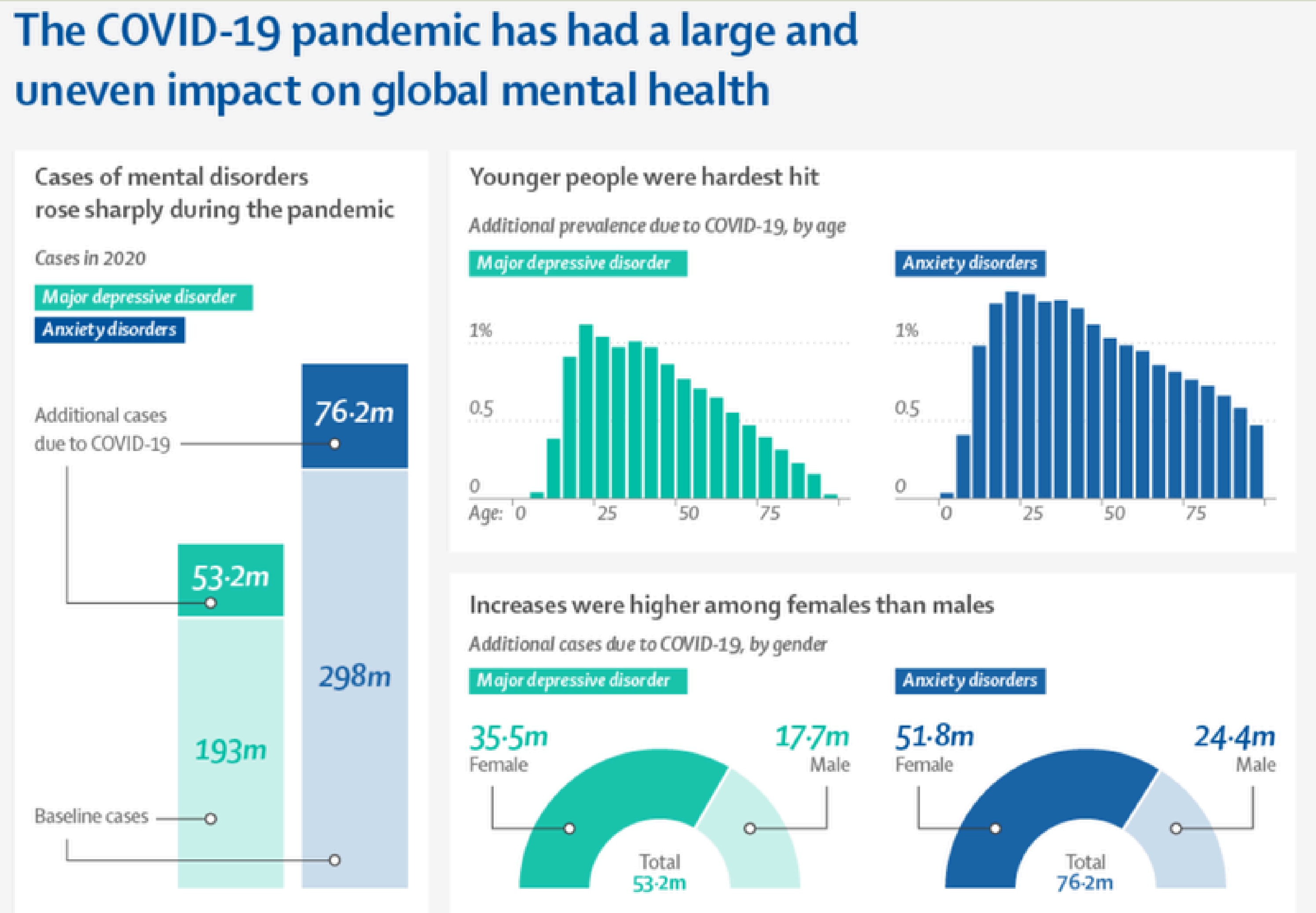
MOTIVATION



Why is mental disorder detection important?

Delayed Diagnosis

Early detection of mental health disorders is crucial for effective intervention. These delays can lead to worsening symptoms and a more challenging treatment process.

Stigma Around Mental Health

Stigma remains a profound barrier in mental health care. Individuals with mental illnesses often face discrimination, leading to social isolation and reluctance to seek help.

Limited Access to Mental Health Professionals

There is a global shortage of mental health professionals, leading to inadequate access to care. This scarcity is particularly pronounced in rural and underserved areas

Applications of AI in Mental Disorder Detection

Clinical Diagnosis Support

AI assists doctors by analyzing patient data, including voice recordings, written text, and facial expressions, to detect mental health conditions like depression, anxiety, and schizophrenia.

Remote Health Monitoring

AI-powered applications continuously monitor users' speech patterns, text messages, and facial expressions to identify subtle behavioral changes. This helps in detecting early symptoms .

Mental Health Chatbots

AI chatbots like Woebot and Wysa provide initial consultations to patients, offering a non-judgmental space to discuss mental health concerns.

Suicide Prevention Systems

AI systems analyze social media posts, voice data, and search history to detect warning signs of suicidal behavior. These systems alert family members, healthcare professionals, or emergency services

MODMA DATASET OVERVIEW

Data Types:

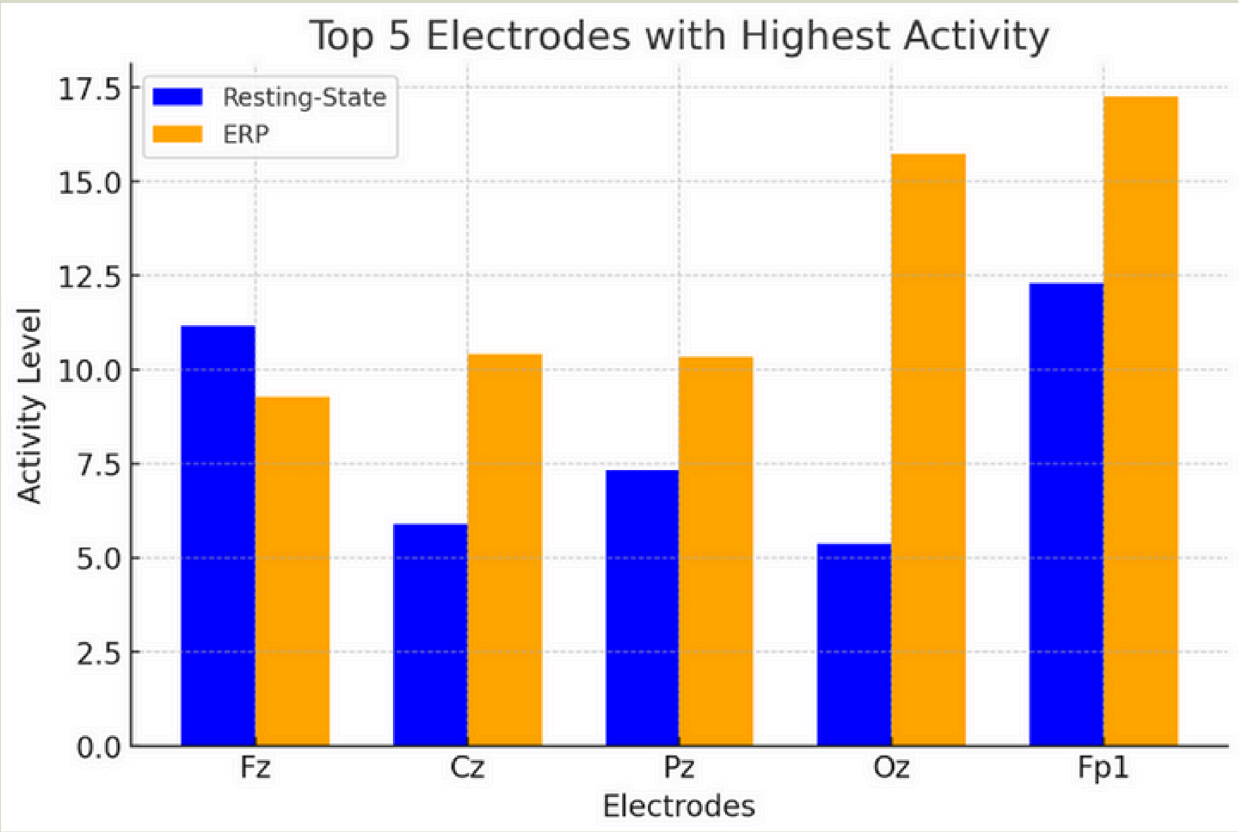
- **Electroencephalography (EEG) Data:**
  - 128-electrode full-brain EEG: Resting-state & Event-Related Potential
  - 3-channel resting-state EEG
- **Audio Data:**
  - Record of Spoken Languages

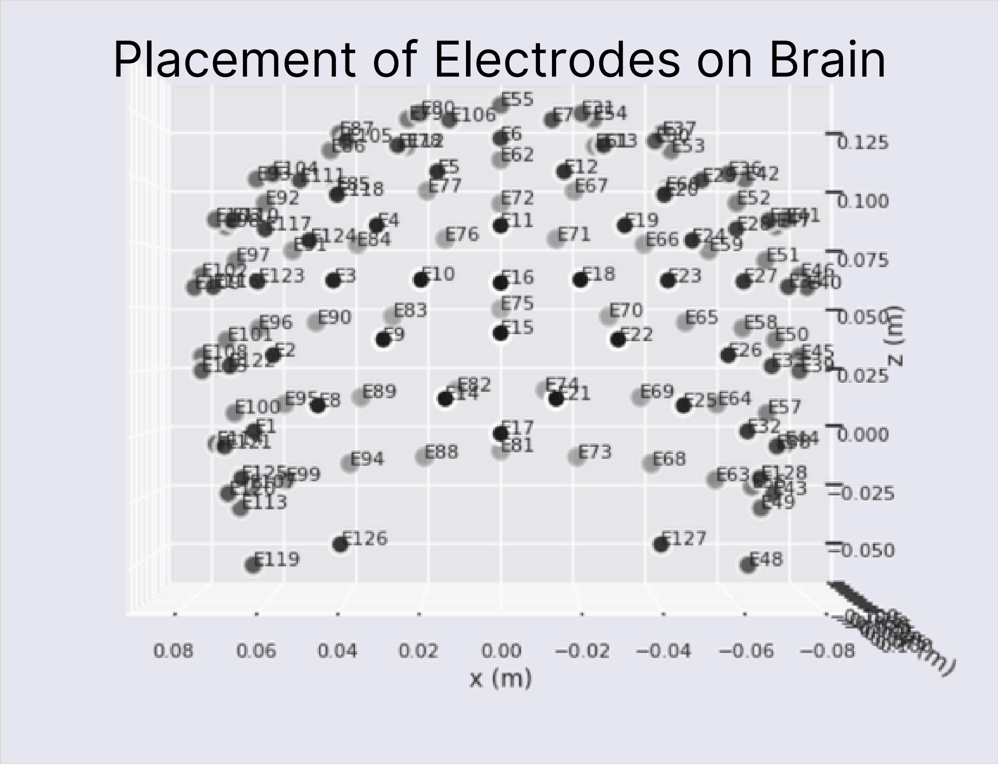
Participants:

- 53 participants for 128-electrode EEG (24 MDD patients and 29 healthy)
- 55 participants for 3-channel EEG (26 MDD patients and 29 healthy)
- 52 participants for Audio Experiment (23 MDD patients and 29 healthy)

Data Collection Protocol:

- EEG signals were recorded using standardized clinical protocols.
- Event-Related Potentials (ERPs) measured using cognitive tasks.
- Audio Signals were recorded in 3 ways. Interview, Reading and Picture description.





Preprocessing and Visualization

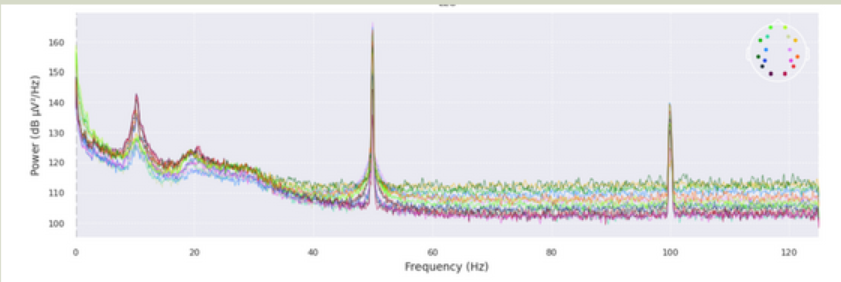
Preprocessing Steps:

- **Noise Removal:** Eliminate artifacts from muscle movement, eye blinks, and electrical
  interference using ICA (Independent Component Analysis).
- **Band-Pass Filtering:** Standardize EEG signals to 0.5-50 Hz.
- **Segmentation & Normalization:** Divide EEG data into time windows and scale features for consistency
- **Frequency-Domain Features**: Extract band power (delta, theta, alpha, beta, gamma waves).

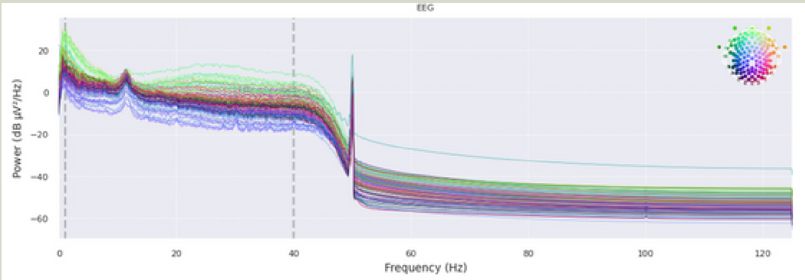
Brain Wave	Frequency (Hz)	Associated Mental State
Delta (δ)	0.5 – 4 Hz	Deep sleep, unconscious states, brain restoration
Theta (θ)	4 – 8 Hz	Light sleep, relaxation, deep meditation, creativity
Alpha (α)	8 – 13 Hz	Calm, relaxed, wakeful rest, meditative states
Beta (β)	13 – 30 Hz	Active thinking, focus, problem-solving
Gamma (γ)	30 – 100 Hz	High-level cognition, learning, memory processing

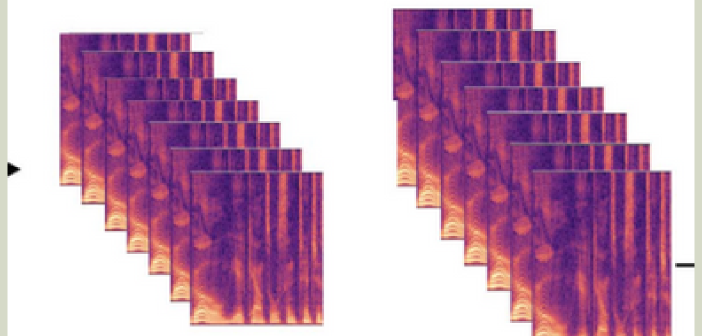
Data Visualization:

- **EEG Signal Plots:** Compare raw vs. filtered time-series EEG signals.
- **Spectrograms**: Analyze frequency-domain activity over time.
- **Topographic Brain Maps**: Visualize brain activity across electrode locations, hence extracting top nodes with most activity.



Band Pass Filtering



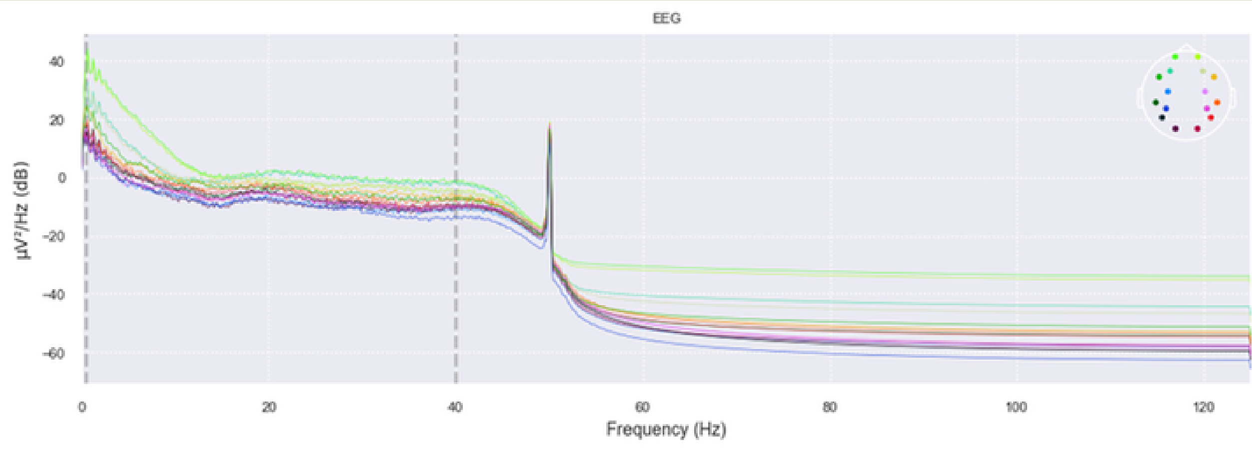


FFT spectrogram

Diagnosing-depression-base-on-EEG-signal (*mylehust*)

MODMA Dataset Preprocessing:

- Focus on 16 key channels for analysis.
- Use Band-Pass filter (0–40 Hz) to extract relevant EEG frequency bands (Delta, Theta, Alpha, Beta).

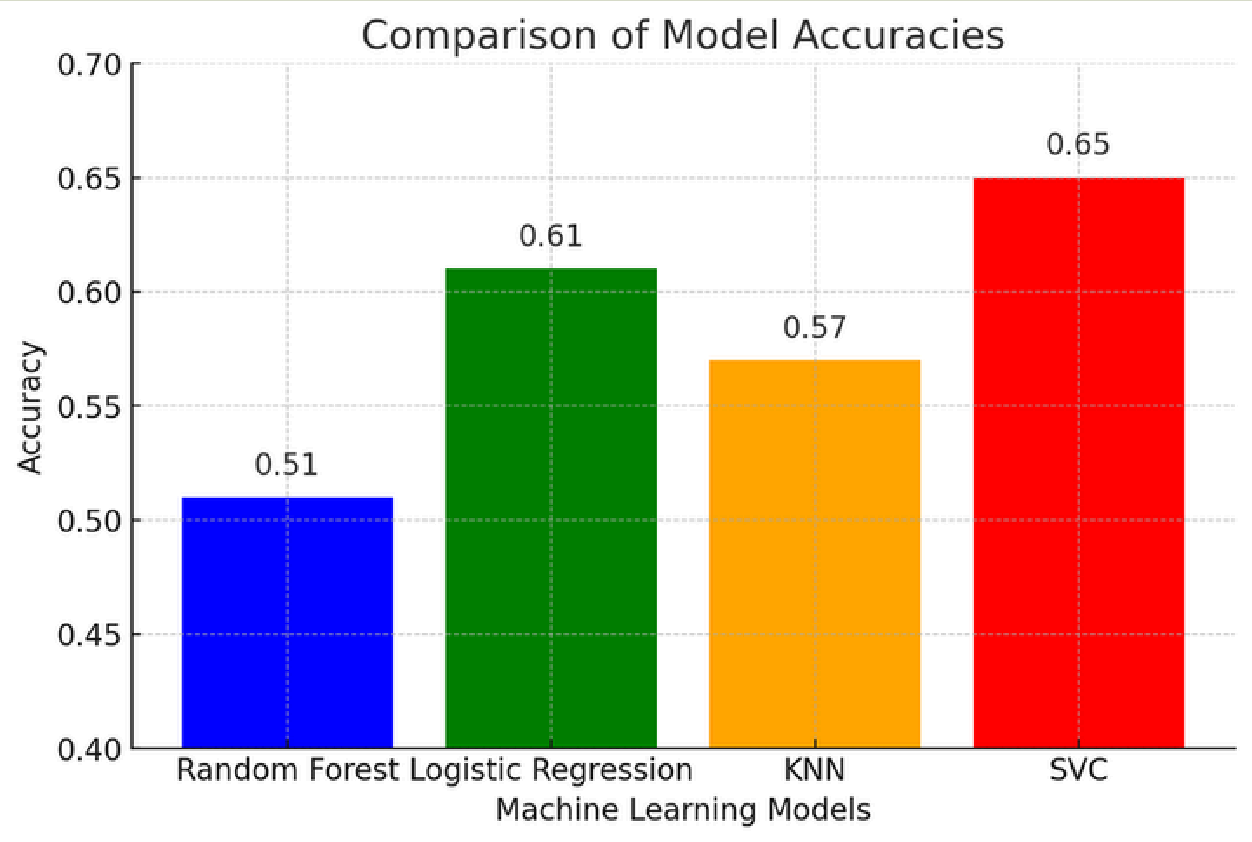


Feature Extraction

- Linear Features:
  - Extract Max, Min, Mean, and Median power from 4 frequency bands.
- Non-Linear Features:
  - Entropy-based features (Spectral entropy, Singular Value Entropy, Permutation Entropy).
- Emotion-Based Analysis:
  - Focus on Fear, Happy, Sad responses and their impact on EEG signals.

Training Model

- Total Features Extracted:
  - 512 Linear Features + 192 Non-Linear Features = 704 Features.
- Machine Learning Models Used:
  - Compared different models, with SVM showing better performance.
- Impact of Band-Pass Filter:
  - Affected 192 features but had minimal impact on model accuracy.



Detecting Depression using EEG

Overview:

- Developed a machine learning model for classifying depression based on EEG signals.
- Utilized the MODMA dataset for training and testing purposes.

Feature Extraction & Preprocessing:

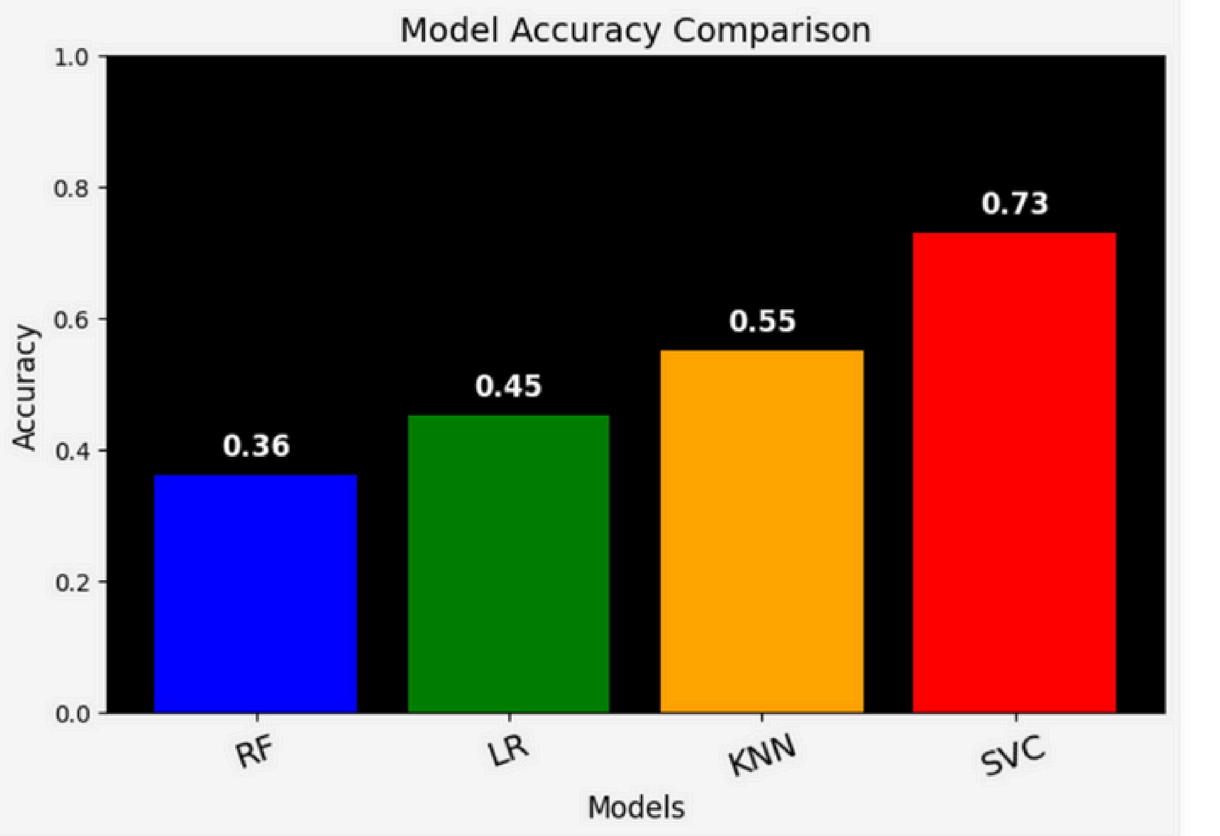
- Eliminated noise in the signals using Band-Pass Filter
- Extracted 8 Linear features like amplitude, power, etc and 2 Non-Linear features like entropy.

Model Building:

- Used Principle Component Analysis (PCA) to extract dominant features
- Implemented 4 machine learning models (Random Forest, Logistic Regression, K Nearest Neighbours and Support Vector Machine)

Results & Outputs:

- Achieved highest accuracy of 73% using SVM
- Model effectively differentiates between depressed and non-depressed individuals.



Github: Diagnosing-depression-using-EEG

Research Gaps / Challenges

Dataset Limitation

The study uses the MODMA dataset, which comprises only 52 subjects. This limited sample size and demographic scope raise questions about the model's generalizability across larger and more diverse populations

Computational Complexity

The framework combines multiple deep learning architectures , which can lead to high computational demands and may impact the feasibility of real-time diagnosis.

Accuracy Limitation

Traditional ML models rely on handcrafted features that miss the complex spatial and temporal dynamics in EEG and speech signals, resulting in lower accuracy. Our deep learning framework automatically learns these intricate patterns, aiming for significantly higher performance.

Reliance on ML Models

This research depends on machine learning approaches that require handcrafted features. This limits their ability to capture the full complexity of EEG and speech signals, resulting in lower accuracy.

Timeline

MARCH : MODEL DEVELOPMENT

This month involves the implementation of various machine learning models, starting with baseline models and progressing to more advanced architectures.

FEBRUARY : RESEARCH & DATA ANALYSIS

The initial phase focuses on thorough research of existing mental disorder detection models, followed by a detailed analysis and preparation of our dataset.

APRIL : TRAINING, EVALUATION & DEPLOYMENT

The final stage involves training and evaluating the selected models using crossvalidation, followed by deploying the bestperforming model for real-time detection.

Deliverables

Enhanced Diagnostic Model

A machine learning along with deep learning-based model utilizing advanced architectures that significantly improves the accuracy of depression detection from EEG and speech signals.

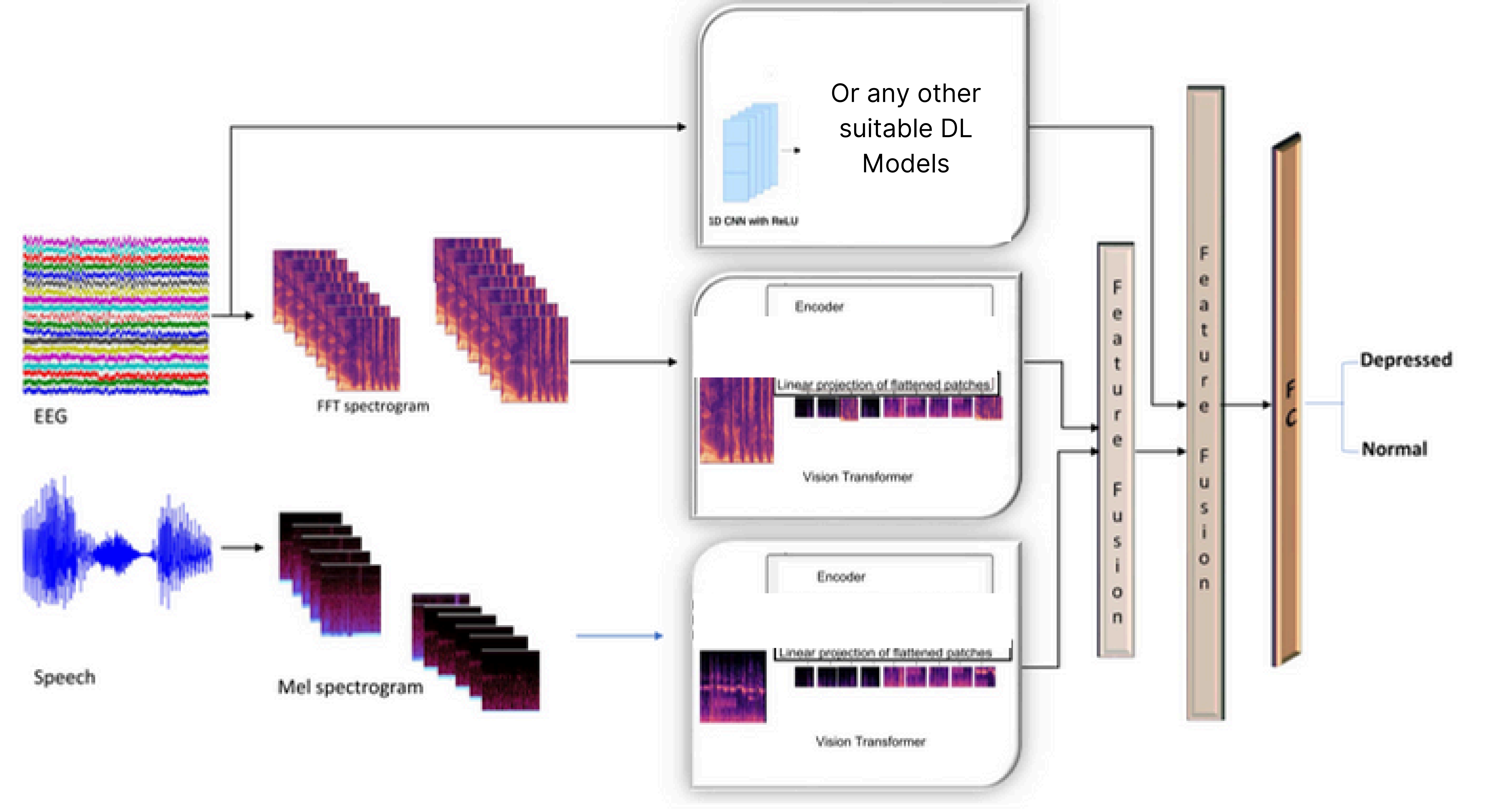
Deployment Prototype

A web-based demonstration tool developed using a lightweight framework for real-time depression diagnosis, showcasing the model's enhanced performance.

Comprehensive Project Report

A detailed report covering the methodology, experimental setup, results, comparative analysis, and discussion of challenges and future directions.

Current Approach and Proposed Solution



Future Work and Conclusion

Future Work

- Enhanced Model Generalization: Expand dataset size and diversity to improve model robustness across different populations.
- Real-Time EEG Processing: Implement real-time signal processing for immediate diagnosis and intervention.
- Multi-Modal Fusion: Integrate additional data sources like speech and facial recognition for more accurate detection.
- Explainable AI (XAI) Integration: Develop interpretable models to enhance trust and usability in clinical settings.
- Edge Computing: Optimize models for deployment on mobile and wearable devices for remote monitoring.

Conclusion

This research highlights the potential of AI-driven mental disorder detection using EEG signals. The proposed approach demonstrates promising results, with SVM achieving the highest accuracy. Despite dataset limitations and computational challenges, future improvements in data collection, model optimization, and real-time deployment can enhance its clinical applicability.

Thank You