Deep Learning-Based Stress and Depression Detection System

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***Abstract*—This project presents a deep learning-based approach for the classification of mental health disorders, specifically stress and depression, using a Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN). The system utilizes Electroencephalogram (EEG) signals as input to capture brain activity patterns associated with different mental states.**

By integrating convolutional layers for spatial feature extraction and recurrent layers for temporal pattern learning, the ESRGAN model effectively analyzes complex EEG data.

The implementation is carried out in MATLAB, incorporating image processing techniques to transform EEG signals into meaningful representations suitable for deep learning classification. The proposed model classifies stress levels into three stages: mild, moderate, and severe, and also detects the presence of depression.

Following classification, the system provides personalized suggestions and recommendations, including lifestyle modifications, stress management techniques, and potential treatment options to help users manage their mental health condition.

This intelligent framework aims to support early detection and intervention, thereby improving mental well-being and reducing the risk of severe psychological disorders. The results demonstrate that the ESRGAN-based approach achieves high accuracy and reliability, making it a promising tool for automated mental health assessment and decision support systems

I. INTRODUCTION

Mental health disorders have emerged as one of the most critical global health challenges, affecting millions of individuals across different age groups and socio-economic backgrounds. Disorders such as stress and depression significantly impact cognitive functioning, motor abilities, and overall quality of life. Traditional diagnostic methods largely rely on clinical assessments, patient history, and manual interpretation of neurological signals, which are often time-consuming, subjective, and prone to human error.

Electroencephalography (EEG) has gained significant importance as a non-invasive and cost-effective technique for monitoring brain activity. EEG signals provide valuable insights into neural dynamics by capturing electrical activity generated by the brain. However, the complexity, non-linearity, and high dimensionality of EEG signals make their interpretation a challenging task.

This study focuses on the development of a deep learning-based framework for the classification of mental health disorders using EEG signal images transformed into spectrograms. The Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) is employed to improve spectrogram image quality, followed by a Decision Tree classifier for final classification of mental health conditions.

1.1 Objective

The primary objective of this research is to design and develop an efficient, accurate, and automated system for the early detection and classification of mental health disorders using EEG signals. The study aims to address the limitations of traditional diagnostic approaches by leveraging advanced deep learning techniques and image processing methods to enhance diagnostic precision and reliability.

1.1.1 Development of an EEG-Based Diagnostic Framework
One of the fundamental objectives is to create a robust framework that utilizes EEG signals as the primary input for detecting neurological disorders. This involves acquiring raw EEG data, preprocessing it to remove noise and artifacts, and transforming it into a suitable format for further analysis. By focusing on EEG signals, the system ensures a non-invasive and patient-friendly diagnostic approach.

1.1.2 Transformation of EEG Signals into Spectrogram Images
Another key objective is to convert raw EEG signals into spectrogram images that represent the frequency distribution of brain activity over time. This transformation enables the capture of both temporal and spectral features, which are essential for identifying distinct patterns associated with different mental health conditions. The use of image-based representations also facilitates the application of deep learning models.

1.1.3 Enhancement of Image Quality Using ESRGAN
Improving the quality of spectrogram images is crucial for accurate feature extraction. Therefore, the study aims to implement the Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) to enhance image resolution and clarity. This step ensures that subtle patterns and features within EEG data are preserved and emphasized, leading to better classification performance.

1.1.4 Feature Extraction Using DTs
The research aims to utilize DT for automatic feature extraction from enhanced spectrogram images. DTs are capable of learning hierarchical representations of data, making them highly effective for identifying complex spatial patterns. This objective focuses on leveraging DT architecture to extract meaningful and discriminative features without manual intervention.

1.1.5 Classification Using a Hybrid Machine Learning Approach
Another important objective is to implement a hybrid classification model that combines DT-based feature extraction with a decision tree classifier. The decision tree is used to categorize the extracted features into different mental health conditions, namely Stress and depression. This hybrid approach aims to improve classification accuracy while maintaining interpretability.

1.1.6 Performance Evaluation and Comparative Analysis
The study also aims to evaluate the performance of the proposed model using appropriate metrics such as accuracy, precision, recall, and F1-score. A comparative analysis with existing EEG-based classification methods is conducted to demonstrate the effectiveness and superiority of the proposed approach.

1.1.7 Development of a Non-Invasive and Automated Diagnostic Tool
A major objective is to design a system that is completely automated and non-invasive, reducing dependency on manual analysis and minimizing diagnostic delays. This contributes to making the system practical for real-world healthcare applications, particularly in environments with limited access to expert neurologists.

1.1.8 Enabling Early Detection and Clinical Decision Support
The ultimate objective of this research is to enable early detection of mental health disorders, which is critical for effective treatment and disease management. By providing accurate and timely diagnostic insights, the system aims to support clinicians in decision-making and facilitate personalized treatment planning for patients.

II. LITERATURE SURVEY

Paper 1
Title: An AI-Based Framework for Interpretable Mental Health Literacy Segmentation and Decision Support
Authors: A. R. Sarode, M. V. Rani, B. Das, U. S, S. Punia
Year: 2025
Abstract: Mental Health Literacy (MHL) is a critical factor influencing individuals' ability to recognize mental health disorders and seek appropriate treatment. This study presents an advanced artificial intelligence-based framework aimed at segmenting individuals into distinct mental health literacy profiles

using interpretable machine learning techniques. The authors conducted a cross-sectional survey involving 385 participants from diverse academic backgrounds to capture variations in knowledge, beliefs, and attitudes toward mental health. Latent Profile Analysis was employed to identify five unique MHL profiles, each representing different levels of awareness and help-seeking behavior. To ensure interpretability, decision tree models such as C5.0, CART, and Conditional Inference Trees were utilized to generate clear and actionable decision rules. The framework also integrates visualization tools through interactive dashboards, enabling stakeholders to analyze patterns effectively. The study emphasizes the importance of modifiable predictors in designing targeted interventions. Overall, the proposed system provides a scalable and transparent decision-support tool that aids policymakers and healthcare professionals in improving mental health awareness and optimizing resource allocation strategies within institutional settings.

Paper 2
Title: Next-Generation Sensor Technologies for Studying Mental Health Authors: C. H. Liu, Y. M. Bennett
Year: 2026
Abstract: This paper explores the evolution of next-generation sensor technologies for mental health monitoring, highlighting their potential in advancing biomedical research and clinical applications. The authors emphasize the growing importance of wearable and implantable sensors in capturing physiological and neurological data continuously. The study identifies electrochemical sensing as a key area requiring further development to enable precise measurement of neurotransmitters and biomarkers associated with mental health conditions. These sensors facilitate synchronized monitoring of brain activity and behavioral patterns, offering deeper insights into neural functioning. The paper also discusses the integration of bioelectronics with real-time monitoring systems, which can significantly enhance diagnostic accuracy and enable personalized treatment approaches. Despite advancements in traditional sensors for vital signs and motion tracking, the authors point out existing limitations in capturing complex mental health indicators. The study encourages interdisciplinary research to bridge these gaps and improve sensing capabilities. Ultimately, the proposed advancements in sensor technologies have the potential to support early diagnosis, continuous monitoring, and the development of closed-loop therapeutic systems for effective mental health management.

Paper 3
Title: Mental Health Prediction from Twitter Content Data Based on Stress Inducing Themes and Quantum Neural Network Classifier
Authors: B. Sathiya, J. A. Renjit
Year: 2025
Abstract: This study introduces an innovative framework for predicting mental health conditions using social media data, specifically Twitter content. The research focuses on identifying stress-inducing themes such as negative emotions, addictive behaviors, and exposure to harmful content. These themes are extracted using advanced topic modeling techniques like BERTopic, while personality traits are analyzed using Sentence-BERT models. An authenticity score is computed to measure discrepancies between self-reported and inferred personality traits, thereby enhancing classification reliability. The core of the framework is a Quantum Neural Network (QNN) classifier, which effectively models complex and non-linear relationships between extracted features. The system demonstrates high performance, achieving accuracy, precision, recall, and F1-scores above 93%. The study also highlights the importance of temporal analysis in tracking mood variations over time, enabling early detection of disorders such as depression, anxiety, bipolar disorder, and PTSD. The proposed approach outperforms traditional deep learning models and provides a scalable solution for large-scale mental health monitoring using digital footprints.

Paper 4
Title: Mixture of Experts for Depression and Anxiety Disorder Prediction from Textual and Non-Textual Social Media Data
Authors: W. Ramos Dos Santos et al.
Year: 2025
Abstract: This paper presents a novel approach for predicting depression and anxiety disorders using a mixture of experts (MoE) framework applied to social media data. The study addresses key challenges in

mental health prediction, including noisy and context-free data, limited use of multimodal inputs, and lack of generalization across datasets. The proposed model integrates textual and non-textual features, leveraging large language models to process unstructured data effectively. By combining multiple expert models, the framework enhances prediction accuracy and robustness. The research evaluates the model on datasets from Twitter and Reddit, covering different languages and contexts. Results demonstrate significant improvements over traditional models, both in machine learning metrics and human expert evaluations. The study also emphasizes the importance of incorporating diverse data sources, such as images and user behavior, to improve predictive performance. Overall, the proposed MoE framework provides a comprehensive and scalable solution for early detection of mental health disorders in real-world scenarios.

Paper 5
Title: Personality Traits and Demographics Analysis in Online Mental Health Discourse
Authors: M. E. Aragón, M. Fernandez-Pichel, D. E. Losada
Year: 2026
Abstract: This study investigates the relationship between personality traits, demographic factors, and mental health conditions using social media data. The research focuses on the Big-5 personality model to analyze behavioral patterns of individuals associated with disorders such as depression, anorexia, gambling, and self-harm. Using the PANDORA dataset, the authors develop machine learning models for personality prediction and author profiling. These models are further applied to various eRisk datasets to validate their effectiveness. The study reveals significant correlations between personality traits and mental health conditions, such as high neuroticism and low extraversion across multiple disorders. Additionally, the research highlights demographic biases in prediction systems, showing variations in accuracy across different age and gender groups. The findings emphasize the importance of considering demographic diversity in mental health models to ensure fairness and reliability. The proposed approach contributes to a deeper understanding of psychological behavior and improves the development of personalized mental health assessment systems.

Paper 6
Title: Mental Health Assessment Model Using Circular q-Rung Orthopair Fuzzy MULTIMOORA Method
Author: G. Ying
Year: 2025
Abstract: This paper proposes a fuzzy decision-making model for mental health assessment using circular q-rung orthopair fuzzy sets integrated with the MULTIMOORA method. The study enhances traditional fuzzy models by incorporating advanced aggregation operators such as weighted Muirhead mean operators. These mathematical tools improve the evaluation of complex and uncertain mental health parameters. The model considers multiple criteria, including engagement, effectiveness, and accessibility, to rank treatment strategies. A real-world case study involving college students is used to validate the model's effectiveness. The results demonstrate improved accuracy and reliability in selecting optimal mental health interventions. Sensitivity analysis confirms the stability of the proposed method under varying conditions. The study highlights the importance of fuzzy logic in handling uncertainty in mental health evaluation and provides a systematic approach for decision-making in healthcare planning.

Paper 7
Title: Hybrid Transformer Architecture for Multiclass Mental Illness Prediction
Authors: A. Karamat et al.
Year: 2025
Abstract: This research introduces a hybrid transformer-based architecture for predicting multiple mental health disorders using social media text data. The model combines MentalBERT and MelBERT, which are specialized pretrained language models designed to capture domain-specific and metaphorical language patterns. These features are further processed using DTs to enhance representation learning. The proposed architecture addresses limitations of traditional models that fail to understand contextual and figurative language in mental health discourse. Experimental results show high accuracy and F1-scores, outperforming existing approaches. The study emphasizes the importance of domain-specific embeddings and advanced deep learning techniques in improving mental illness prediction.

Paper 8
Title: Mental Health Index (MHI): A Personalized Multi-Task Deep Learning Framework
Authors: A. Paul, K. Dhanushkodi, S. Alphonse
Year: 2025
Abstract: This paper presents the Mental Health Index (MHI), a personalized deep learning framework for real-time mental health monitoring. The system integrates physiological signals such as heart rate variability, respiration rate, and skin response with behavioral data. A multi-task GRU network is used to process these inputs and generate mental health scores. Personalization is achieved through baseline calibration using anomaly detection techniques. The framework also includes explainable AI components to enhance transparency. Experimental results demonstrate high accuracy and stability. The proposed system supports continuous monitoring and personalized healthcare applications.

Paper 9
Title: Emotion-Aware Ensemble Learning for Mental Health Diagnosis
Authors: G. Yadav et al.
Year: 2025
Abstract: This study proposes an ensemble learning framework for mental health diagnosis using multimodal data. The system integrates facial expressions and typing patterns to assess emotional states. Multiple classifiers, including SVM, DT, and Random Forest, are combined to improve prediction accuracy. The model achieves high performance across evaluation metrics. The study highlights the importance of combining different data sources for comprehensive mental health analysis and suggests future integration with physiological signals.

Paper 10
Title: MindWellQA: Evidence-Based QA System for Psychological Disorders
Authors: D. Pawar, S. Phansalkar
Year: 2025
Abstract: This paper introduces MindWellQA, a question-answering system designed for psychological disorders using large language models. The system integrates medical knowledge bases and uses techniques such as intent classification and named entity recognition to provide accurate responses. It employs transfer learning and fine-tuning methods to improve performance. The system is evaluated using both quantitative and qualitative metrics and validated by experts. Results show high accuracy and reliability, making it a useful tool for mental health awareness and support.

III. SYSTEM ANALYSIS

System analysis is a crucial phase in the development of any intelligent healthcare solution, as it provides a clear understanding of the current methodologies, their limitations, and the need for improved systems. In the domain of mental health disorder detection, especially using EEG signals, traditional approaches have struggled to achieve high accuracy and reliability due to the complex nature of brain signals. This chapter presents a detailed analysis of the existing systems, identifies their limitations, and introduces the proposed deep learning-based framework designed to overcome these challenges.

3.1 Existing System

The existing systems for detecting mental health disorders such as Stress and depression primarily rely on conventional diagnostic techniques and basic machine learning models. In clinical practice, diagnosis is often performed through neurological examinations, cognitive assessments, imaging techniques like manual interpretation of EEG signals by trained professionals. While these approaches provide valuable insights, they are largely dependent on human expertise and are prone to subjectivity and variability.

In the context of computational methods, traditional EEG-based systems typically involve manual feature extraction followed by classification using machine learning algorithms such as Support Vector Machines, k-Nearest Neighbors, or basic neural networks. These systems require domain knowledge to identify relevant features from raw EEG signals, including statistical, frequency-based, or time-domain characteristics. Although these handcrafted features can capture certain aspects of brain activity, they often fail to represent the full complexity of EEG signals, leading to limited performance.

Moreover, many existing approaches process raw EEG signals directly without transforming them into more interpretable formats. This restricts the ability of models to capture both temporal and spectral information effectively. Additionally, image-based techniques, when used, often rely on low-resolution representations that do not preserve fine-grained details necessary for accurate classification. As a result, these systems struggle to differentiate between similar neurological conditions.

Another limitation of existing systems is their reliance on single-model architectures. Many models are designed using either traditional machine learning or deep learning independently, without leveraging the strengths of hybrid approaches. This often results in suboptimal performance, particularly when dealing with high-dimensional and noisy EEG data. Furthermore, the lack of interpretability in some deep learning models reduces their acceptance in clinical environments, where transparency and explain ability are essential.

3.1.1 Disadvantages

The existing systems suffer from several critical limitations that hinder their effectiveness in real-world applications. One of the major disadvantages is the dependence on manual feature extraction, which requires significant domain expertise and may lead to inconsistent results. Since EEG signals are highly complex and non-linear, handcrafted features are often insufficient to capture subtle patterns associated with different mental health disorders.

Another significant drawback is the low accuracy and generalization capability of traditional machine learning models. These models are not well-suited for handling large-scale and high-dimensional data, resulting in poor performance when applied to diverse datasets. Additionally, the inability to effectively capture both temporal and frequency-domain information further limits their diagnostic capability.

Existing systems also face challenges related to data quality and representation. The use of raw EEG signals without appropriate transformation or enhancement leads to noise and loss of important information. When spectrograms or other visual representations are used, they are often not optimized for feature extraction, resulting in reduced classification performance.

The lack of advanced image enhancement techniques is another limitation. Without methods such as super-resolution, important fine details in EEG-derived images may be lost, affecting the ability of models to distinguish between similar disorders. Furthermore, most systems do not incorporate hybrid architectures that combine the strengths of deep learning and traditional classifiers, leading to missed opportunities for performance improvement.

Finally, many existing solutions lack automation and scalability. They often require significant human intervention, making them time-consuming and unsuitable for real-time applications. The absence of robust and interpretable decision-making mechanisms also limits their adoption in clinical settings, where reliability and transparency are critical.

3.2 Proposed System

The proposed system introduces a novel and efficient framework for the classification of mental health disorders using EEG signal images enhanced through advanced deep learning techniques. Unlike traditional approaches, this system transforms raw EEG signals into spectrogram images, enabling the capture of both temporal and spectral characteristics of brain activity. This transformation significantly improves the representation of EEG data and makes it suitable for image-based analysis.

To further enhance the quality of these spectrogram images, the system employs the Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN). This technique improves image resolution and clarity, ensuring that fine-grained details are preserved and emphasized. By enhancing the visual quality of input data, the system enables more effective feature extraction and improves overall classification performance.

The core of the proposed framework is a hybrid model that combines ESRGAN and a decision tree classifier. The DT is responsible for automatically extracting hierarchical spatial features from the enhanced spectrogram images. These features capture complex patterns and relationships within the data that are difficult to identify using traditional methods. The extracted features are then passed to a decision tree classifier, which performs the final classification of mental health disorders. This combination leverages the powerful feature learning capability of DTs and the interpretability of decision trees.

The system is designed to classify multiple mental health conditions, including Stress and depression. It is trained and evaluated using relevant EEG datasets, demonstrating high accuracy, robustness, and generalization capability. The proposed framework is fully automated, reducing the need for manual intervention and enabling faster diagnosis.

In addition to its technical advantages, the system is non-invasive, making it safe and comfortable for patients. It also supports scalability, allowing deployment in real-time healthcare environments. The integration of advanced deep learning techniques and hybrid classification strategies makes the proposed system a powerful tool for modern medical diagnostics.

3.2.1 Advantages

The proposed system offers several significant advantages over existing approaches, making it a highly effective solution for mental health disorder classification. One of the key advantages is the use of spectrogram images, which provide a comprehensive representation of EEG signals by capturing both temporal and frequency-domain information. This enhances the ability of the model to identify complex patterns associated with different neurological conditions. Another major advantage is the incorporation of ESRGAN for image enhancement. By improving the resolution and quality of spectrogram images, the system ensures that important details are preserved, leading to more accurate feature extraction and classification. This addresses one of the major limitations of existing systems related to poor data representation.

The use of a hybrid DT and decision tree model further enhances system performance. DTs enable automatic and efficient feature extraction, eliminating the need for manual feature engineering. At the same time, the decision tree classifier provides clear and interpretable decision-making, which is essential for clinical applications. The proposed system also demonstrates high accuracy, robustness, and generalization capability, making it suitable for real-world deployment. Its automated nature reduces dependency on human expertise, saving time and resources. Additionally, the system is scalable and can be integrated into real-time monitoring environments.

Finally, the non-invasive nature of EEG-based diagnosis ensures patient safety and comfort. The ability to detect mental health disorders at an early stage enables timely intervention and improves treatment outcomes. Overall, the proposed system represents a significant advancement in the field of intelligent healthcare and has the potential to greatly assist clinicians in diagnosis and decision-making.

IV. SYSTEM REQUIREMENTS

The successful implementation of a deep learning-based mental health disorder classification system requires a well-defined set of hardware and software resources. These requirements ensure that the system operates efficiently, processes large volumes of EEG data, and supports advanced computational tasks such as image processing, deep learning model training, and evaluation. Since the proposed framework involves converting EEG signals into spectrogram images, enhancing them using super-resolution techniques, and performing classification using hybrid models, the computational demand is relatively high. Therefore, careful selection of system requirements is essential to achieve optimal performance, accuracy, and scalability.

This chapter outlines the necessary hardware and software specifications required to develop and execute the proposed system. The hardware configuration focuses on a laptop-based setup suitable for development and experimentation, while the software requirements emphasize the use of MATLAB and image processing tools to implement the proposed methodology.

4.1 Hardware and Software Specification

The implementation of the proposed system is designed to be cost-effective and accessible, making use of a standard high-performance laptop configuration. The system must be capable of handling data preprocessing, spectrogram generation, image enhancement, and deep learning model training without significant performance bottlenecks. Additionally, the software environment must support advanced numerical computation, image processing, and machine learning functionalities.

4.1.1 Hardware Requirements

The hardware requirements for the proposed system are centered around a laptop configuration that provides sufficient computational power to handle intensive data processing and deep learning tasks. The processor plays a critical role in executing complex algorithms and handling multitasking efficiently. A modern multi-core processor such as an Intel Core i5, Intel Core i7, or equivalent AMD Ryzen processor is recommended to ensure smooth performance during training and testing phases.

Memory capacity is another important factor, as EEG data processing and image-based deep learning models require substantial RAM for efficient execution. A minimum of 8 GB RAM is required for basic operations; however, 16 GB RAM is strongly recommended to achieve better performance, especially when working with large datasets and high-resolution spectrogram images. Increased memory capacity helps in reducing processing delays and prevents system crashes during intensive computations.

Storage requirements are also significant, as the system needs to store raw EEG datasets, generated spectrogram images, enhanced images, trained models, and output results. A minimum of 512 GB storage is recommended, preferably using a Solid-State Drive (SSD), which offers faster data access speeds compared to traditional Hard Disk Drives (HDD). Faster storage improves data loading times and overall system responsiveness.

The graphics processing capability of the laptop can further enhance performance, particularly for deep learning tasks. While integrated graphics are sufficient for basic implementation, a dedicated GPU such as NVIDIA GeForce series is beneficial for accelerating model training and image processing operations. GPU support significantly reduces computation time and enables efficient handling of complex neural network architectures.

Additionally, the laptop should include a high-resolution display for clear visualization of spectrogram images and model outputs. Standard input and output devices such as keyboard, mouse, and display interfaces are required for user interaction and system operation. Overall, the hardware configuration should provide a balanced combination of processing power, memory, and storage to support the complete workflow of the proposed system.

4.1.2 Software Requirements

The software requirements for the proposed system focus primarily on the use of MATLAB as the development environment, along with its image processing capabilities. MATLAB provides a comprehensive platform for numerical computation, data analysis, and algorithm development, making it highly suitable for implementing EEG signal processing and deep learning models.

MATLAB offers built-in toolboxes that support signal processing, image processing, and machine learning, which are essential for this project. The Signal Processing Toolbox is used to handle raw EEG data, perform filtering, and generate spectrograms that represent the frequency distribution of signals over time. This transformation is a critical step in converting EEG signals into image format suitable for deep learning models.

The Image Processing Toolbox in MATLAB plays a vital role in enhancing and analyzing spectrogram images. It provides a wide range of functions for image enhancement, filtering, resizing, and feature extraction. These functionalities are essential for preparing high-quality input data for the classification model. Additionally, MATLAB supports the implementation of advanced techniques such as super-resolution, which can be used to improve image clarity and detail.

For deep learning model development, MATLAB’s Deep Learning Toolbox enables the design, training, and evaluation of DTs. It provides pre-built layers, training algorithms, and visualization tools that simplify the implementation of complex neural network architectures. The toolbox also supports integration with GPU hardware, allowing faster computation and improved performance.

Furthermore, MATLAB provides an interactive environment for data visualization, enabling users to analyze results effectively through graphs, plots, and images. This helps in evaluating model performance and understanding classification outcomes.

In summary, the combination of MATLAB and its image processing capabilities provides a powerful and flexible software environment for implementing the proposed system. It supports all stages of development, from data preprocessing and image enhancement to model training and evaluation, ensuring a seamless and efficient workflow.

V. SYSTEM DESIGN

5.1 System Architecture

The system architecture is designed as a multi-stage pipeline that systematically processes EEG data to produce accurate classification outcomes. It begins with the acquisition of raw EEG signals. Preprocessing removes unwanted noise and enhances signal quality. The cleaned EEG signals are then transformed into spectrogram images. The ESRGAN module improves their resolution. A Decision Tree extracts hierarchical features, and a Decision Tree classifier performs final classification into Stress or Depression categories.

5.2 Architecture Diagram

The architecture diagram illustrates the flow of data from raw EEG signal input through preprocessing, spectrogram generation, ESRGAN enhancement, DT feature extraction, and final Decision Tree classification. Fig 5.1 shows the architectural diagram of this project.

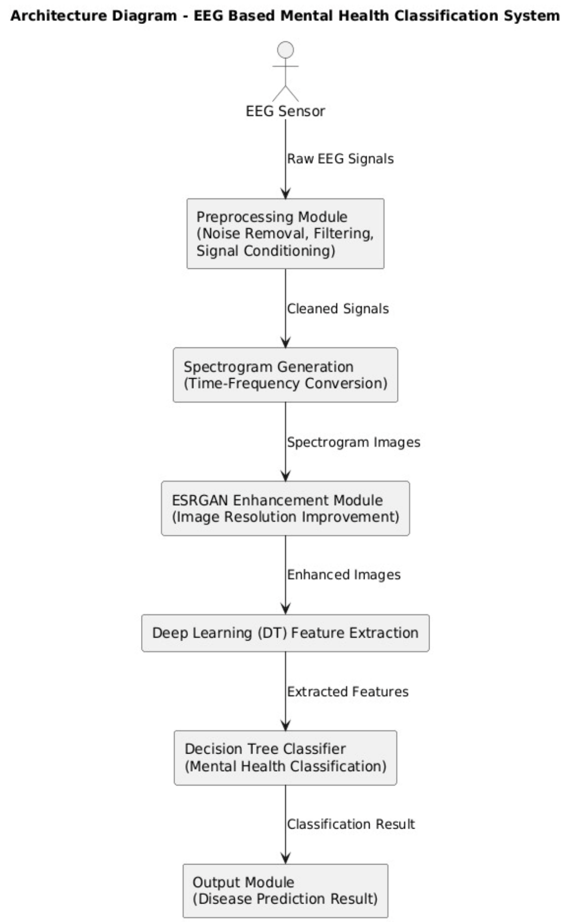

Fig 5.1 – System Architecture Diagram

5.3 Dataflow Diagram

The dataflow diagram (DFD) provides a detailed representation of how data moves through the system from raw EEG signal input through preprocessing, spectrogram generation, ESRGAN image enhancement, DT feature extraction, and Decision Tree classification. Fig 5.2 shows the data flow between each component.

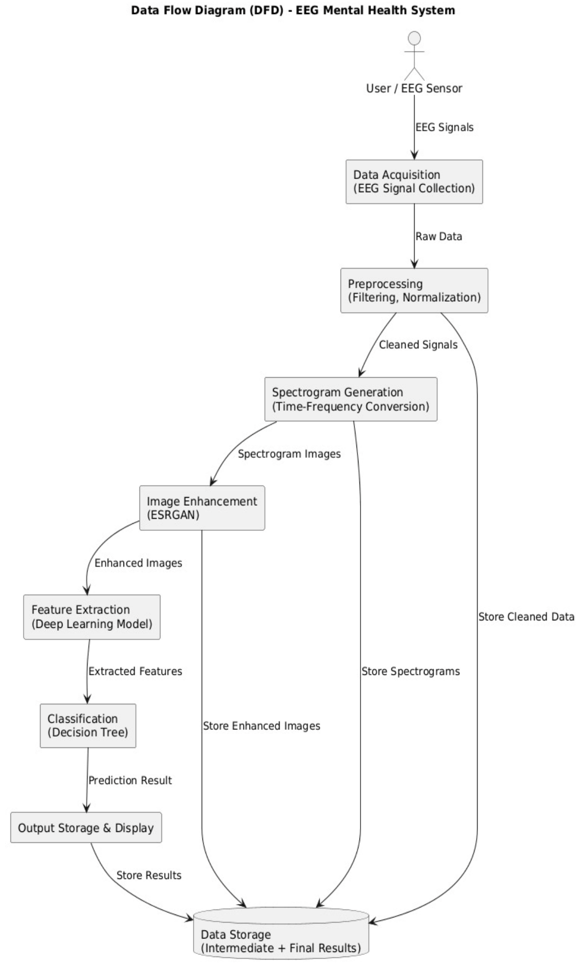

Fig 5.2 – Data Flow Diagram

VI. SYSTEM IMPLEMENTATION

6.1 Introduction

System implementation is the phase where the conceptual design of the proposed framework is transformed into a working model capable of performing real-time classification of mental health disorders. The implementation focuses on integrating signal processing, image transformation, deep learning, and machine learning techniques into a unified pipeline. The proposed system is developed to process EEG signals, convert them into spectrogram images, enhance their quality, extract meaningful features, and finally classify them into specific mental health conditions such as Stress and depression.

The implementation is carried out using MATLAB, which provides a comprehensive environment for signal processing, image analysis, and deep learning model development. The workflow begins with EEG

signal acquisition and pre-processing, followed by spectrogram generation. The generated images are enhanced using ESRGAN to improve resolution and feature clarity. A DT is then used to automatically extract spatial features from the enhanced images. These features are passed to a decision tree classifier for final classification.
The system is designed to be modular, allowing each component to function independently while maintaining seamless integration with other modules. This modular structure improves flexibility, scalability, and ease of debugging. The implementation ensures that the system is automated, minimizing human intervention and enabling faster and more reliable diagnosis.

6.2 System Modules
The proposed system is divided into the following major modules:

- EEG Data Acquisition and Preprocessing Module
- Spectrogram Generation Module
- Image Enhancement Module (ESRGAN)
- Feature Extraction Module (DT)
- Classification Module (Decision Tree)

6.3 Module Description
EEG Data Acquisition and Preprocessing Module
This module is responsible for collecting raw EEG signals and preparing them for further processing. It ensures that the input data is clean, consistent, and suitable for transformation into image format.
The first function of this module involves acquiring EEG signals from datasets or sensors, ensuring that the data represents brain activity accurately under different mental health conditions. The signals are stored in a structured format for easy access and processing.
The module performs noise removal using filtering techniques to eliminate artifacts caused by muscle movement, eye blinking, or external interference. This step is essential to improve signal quality and prevent inaccurate feature extraction.
Normalization is applied to standardize the EEG signals, ensuring that variations in amplitude do not affect subsequent processing stages. This improves the consistency of data across different samples.
Segmentation of EEG signals into smaller time windows is performed to capture localized temporal patterns. This enables the system to analyze short-duration brain activity more effectively.
Finally, the pre-processed signals are validated to ensure that they meet the required quality standards before being passed to the next module.

Spectrogram Generation Module
This module converts pre-processed EEG signals into spectrogram images, enabling the extraction of both temporal and frequency-domain features.
The module applies time-frequency analysis techniques such as Short-Time Fourier Transform (STFT) to transform one-dimensional EEG signals into two-dimensional spectrogram representations. This allows visualization of how signal frequency changes over time.
Spectrogram images capture important patterns that are not easily identifiable in raw signals, providing a richer representation of brain activity. This enhances the ability of the system to distinguish between different disorders.
The module ensures proper scaling and resolution of generated images to maintain consistency across the dataset. Uniform image dimensions are critical for deep learning model training.
Color mapping techniques are applied to improve visual contrast, making important frequency components more distinguishable. This step enhances feature visibility for subsequent processing.
The generated spectrogram images are stored and forwarded to the image enhancement module for further refinement.

Image Enhancement Module (ESRGAN)
This module improves the quality and resolution of spectrogram images using the ESRGAN
The ESRGAN model enhances low-resolution spectrogram images by reconstructing high-frequency details that are often lost during initial image generation. This leads to sharper and more detailed images.
The module focuses on preserving fine-grained features, which are crucial for accurate classification of mental health disorders. Improved image clarity directly impacts feature extraction performance.
Adversarial learning is used to train the ESRGAN model, where a generator and discriminator work together to produce realistic high-resolution images.

The enhanced images are evaluated to ensure that noise is not amplified during the enhancement process. Quality control mechanisms are applied to maintain reliability.
Finally, the high-resolution images are passed to the feature extraction module, providing better input for deep learning models.

Feature Extraction Module (DT)
This module uses DTs to automatically extract meaningful features from enhanced spectrogram images.
The DT processes input images through multiple convolutional layers, which detect patterns such as edges, textures, and complex structures. These features represent important characteristics of EEG signals.
Pooling layers are used to reduce dimensionality while retaining essential information, improving computational efficiency and preventing overfitting.
Activation functions introduce non-linearity, enabling the model to learn complex relationships within the data. This improves the model's ability to distinguish between similar patterns.
The fully connected layers combine extracted features into a compact representation suitable for classification. This ensures that only relevant information is passed forward.
The output of this module is a set of high-level feature vectors that are used by the classification module for final decision-making.

Classification Module (Decision Tree)
This module performs the final classification of mental health disorders based on features extracted by the DT.
The decision tree classifier analyzes feature vectors and applies hierarchical decision rules to categorize input data into Stress and Depression.
The model is trained using labeled data, enabling it to learn patterns associated with each disorder. This improves classification accuracy and reliability. Decision trees provide interpretability, allowing users to understand how classification decisions are made. This is particularly important in healthcare applications. The module evaluates classification performance using metrics such as accuracy, precision, recall, and F1-score to ensure effectiveness.
The final output is generated as a predicted class label, which can be used for further analysis or clinical decision support.

6.4 Algorithm
The overall algorithm of the proposed system describes the step-by-step process involved in classifying mental health disorders using EEG signal images.
Initially, raw EEG signals are collected from the dataset and passed to the preprocessing stage, where noise removal, normalization, and segmentation are performed to improve signal quality. The cleaned signals are then transformed into spectrogram images using time-frequency analysis techniques.
The generated spectrogram images are enhanced using ESRGAN to improve resolution and highlight important features. These enhanced images are then fed into a DT, which extracts hierarchical spatial features automatically.
The extracted features are passed to a decision tree classifier, which analyzes them and assigns the input to one of the predefined categories: Stress and Depression. The classification result is then produced as the final output.
The system iterates through all input samples, evaluates performance metrics, and stores results for analysis. This algorithm ensures a systematic and efficient approach to mental health disorder classification, providing accurate and reliable outcomes.

VII. SOFTWARE ENVIRONMENT

The software environment plays a crucial role in the successful development and execution of the proposed mental health disorder classification system. Since the system involves complex signal processing, image transformation, deep learning, and classification tasks, a powerful and flexible computational platform is required. In this work, MATLAB is selected as the primary software environment due to its extensive support for numerical computation, visualization, and machine learning. MATLAB provides an integrated ecosystem that simplifies the implementation of each stage of the system, from EEG signal preprocessing to final classification.
The use of MATLAB ensures efficient handling of multidimensional data, seamless integration of various

toolboxes, and availability of built-in functions for rapid development. It also supports graphical visualization, which is essential for analyzing EEG signals and spectrogram images. This chapter describes the software environment in detail, focusing on MATLAB features, toolboxes, and their role in implementing the proposed framework.

7.1 Overview of Matlab Environment

MATLAB is a high-level programming environment widely used for engineering, scientific research, and data analysis applications. It provides a user-friendly interface that allows developers to perform complex computations using simple commands and scripts. MATLAB supports matrix-based operations, making it highly suitable for processing EEG signals, which are inherently multidimensional.

The environment includes an interactive command window, script editor, workspace viewer, and visualization tools, enabling users to develop, debug, and analyze programs efficiently. MATLAB also supports integration with hardware devices and external datasets, which is useful for EEG data acquisition and processing. Its ability to handle large datasets and perform real-time computations makes it an ideal choice for implementing the proposed system.

7.2 Signal Processing Capabilities

One of the key requirements of the proposed system is the processing of raw EEG signals. MATLAB provides powerful signal processing capabilities through its dedicated toolboxes. These tools enable filtering, transformation, and analysis of signals with high precision.

The software supports various filtering techniques, including low-pass, high-pass, and band-pass filters, which are essential for removing noise and artifacts from EEG signals. It also provides functions for Fourier Transform and Short-Time Fourier Transform, which are used to convert signals into spectrogram representations. These capabilities ensure that the EEG data is accurately processed and prepared for further analysis.

MATLAB’s signal visualization tools allow users to plot waveforms and analyze signal characteristics in both time and frequency domains. This helps in understanding the nature of EEG signals and validating preprocessing steps before moving to the next stage.

7.3 Image Processing Environment

MATLAB Image Processing Toolbox plays a vital role in handling spectrogram images generated from EEG signals. This toolbox provides a wide range of functions for image enhancement, filtering, resizing, and transformation.

The toolbox enables conversion of processed signals into high-quality spectrogram images, which are used as input for deep learning models. It supports operations such as contrast enhancement, noise reduction, and normalization, which improve the quality of images before feature extraction.

Additionally, MATLAB allows manipulation of image matrices, enabling developers to apply custom algorithms such as ESRGAN-based enhancement. Visualization functions help in displaying and comparing original and enhanced images, ensuring that the enhancement process is effective.

7.4 Deep Learning Support

MATLAB Deep Learning Toolbox provides comprehensive support for designing and training deep learning models such as DTs. This toolbox includes predefined layers, training algorithms, and optimization techniques that simplify the development of complex neural network architectures.

The toolbox allows users to create DT models for feature extraction from spectrogram images. It supports automatic differentiation, which enables efficient training of deep networks. Various training options such as learning rate, batch size, and epochs can be customized to achieve optimal performance.

MATLAB also provides tools for evaluating model performance, including accuracy plots, confusion matrices, and loss curves. These features help in analyzing the effectiveness of the trained model and making necessary improvements.

7.5 Machine Learning and Classification Tools

MATLAB Statistics and Machine Learning Toolbox is used for implementing the decision tree classifier in the proposed system. This toolbox provides functions for training, testing, and validating machine learning models.

The decision tree classifier is developed using built-in functions that allow easy creation of classification models. The toolbox also supports feature selection, cross-validation, and performance evaluation, ensuring that the model is robust and reliable.

Visualization tools within the toolbox enable representation of decision trees, making it easier to interpret classification results. This is particularly important in healthcare applications, where transparency and explainability are essential.

7.6 Data Visualization and Analysis

MATLAB provides powerful data visualization capabilities that help in analyzing EEG signals, spectrogram images, and classification results. Graphical tools such as plots, histograms, and heatmaps allow users to interpret data effectively.

Visualization is used at multiple stages of the system, including signal preprocessing, spectrogram generation, and model evaluation. It helps in identifying patterns, detecting anomalies, and validating system performance.

The ability to generate high-quality visual outputs makes MATLAB an effective tool for presenting results in research and clinical settings. It also aids in debugging and improving the system by providing clear insights into data behavior.

7.7 Advantages of Matlab Environment

The MATLAB software environment offers several advantages for implementing the proposed system. It provides an integrated platform that combines signal processing, image processing, and machine learning capabilities. This eliminates the need for multiple software tools and simplifies development.

The availability of built-in functions and toolboxes reduces development time and effort. MATLAB's user-friendly interface makes it accessible even for users with limited programming experience. Its support for GPU acceleration enhances computational efficiency, especially for deep learning tasks.

Furthermore, MATLAB ensures high accuracy and reliability in numerical computations, which is essential for medical applications. Its strong visualization capabilities and support for algorithm development make it a powerful tool for research and development in mental health diagnostics.

In conclusion, the MATLAB-based software environment provides a comprehensive and efficient platform for implementing the proposed deep learning framework. Its advanced capabilities in signal processing, image enhancement, and machine learning ensure that the system achieves high performance, accuracy, and reliability in classifying mental health disorders using EEG signal images.

VIII. TESTING

8.1 Testing Objective

- Identification of Bugs and Errors
- Quality Product Delivery
- Justification with Requirements
- Offers Confidence in System Reliability
- Enhances System Growth and Scalability

8.2 Testing Methodology

The testing methodology follows a structured and systematic approach involving multiple levels of testing, starting from individual modules and progressing to the complete system.

8.2.1 Unit Testing

Unit testing focuses on testing individual modules independently. Modules such as EEG preprocessing, spectrogram generation, image enhancement, DT feature extraction, and Decision Tree classification are tested separately with controlled input data compared against expected results.

8.2.2 Integration Testing

Integration testing verifies that different modules work together seamlessly, ensuring the output of one module correctly serves as input to the next. Data flow consistency, interface compatibility, and synchronization between modules are checked and validated.

8.2.3 Validation Testing

Validation testing ensures the system meets specified requirements using real EEG datasets. Performance metrics including accuracy, precision, recall, and F1-score are calculated, confirming the system distinguishes between stress and depression with high reliability.

8.2.4 Acceptance Testing

Acceptance testing determines whether the system is ready for real-world deployment, evaluating ease of use, response time, output clarity, and overall usability from the perspective of end users such as clinicians and researchers.

8.2.5 Functional Testing
Functional testing verifies that each function operates according to its intended purpose, checking accuracy of EEG preprocessing, correctness of spectrogram generation, effectiveness of image enhancement, and reliability of classification across different input scenarios.

8.2.6 System Testing
System testing evaluates the complete system using large datasets to assess scalability, processing speed, robustness, and validation that all functional and non-functional requirements are met.

8.2.7 White Box Testing
White Box Testing examines the internal structure and logic of the system. Developers analyze the implementation of each module ensuring all paths, conditions, and loops execute correctly, particularly verifying algorithms used in preprocessing, feature extraction, and classification.

WHITE BOX TESTING APPROACH

TESTER → [Internal/External Module] → RESULT

Fig 8.1 - White Box Testing Approach

8.2.8 Black Box Testing
Black Box Testing evaluates the system based on its input and output without considering internal implementation details. Various EEG inputs are provided and output classifications are analyzed for correctness, identifying functional errors from the user's perspective.

BLACK BOX TESTING APPROACH

TESTER → [Internal/External Module] → RESULT

Fig 8.2 - Black Box Testing Approach

IX. CONCLUSION

The rapid advancement of artificial intelligence and biomedical signal processing has opened new possibilities for improving the diagnosis of mental health disorders. This project has successfully developed a deep learning-based framework for the classification of neurological conditions such as Stress and depression using EEG signal images. The proposed system addresses the limitations of traditional diagnostic methods by introducing an automated, non-invasive, and highly accurate approach.

The system effectively transforms raw EEG signals into spectrogram images, enabling the capture of both temporal and spectral characteristics of brain activity. The application of Enhanced Super-Resolution Generative Adversarial Networks significantly improves the quality of these images, ensuring that fine-grained features are preserved. This enhancement plays a crucial role in improving the performance of the classification model.

The integration of DTs for feature extraction and a decision tree classifier for final decision-making provides a powerful hybrid approach. This combination not only improves classification accuracy but also enhances interpretability, which is essential in medical applications. The system demonstrates strong robustness and generalization capability, making it suitable for real-world deployment.

Overall, the proposed framework provides an efficient and reliable tool for early detection of mental health disorders. It has the potential to assist clinicians in diagnosis, reduce manual workload, and support personalized treatment planning. The system represents a significant step toward intelligent healthcare solutions that leverage advanced computational techniques for improved patient outcomes.

9.1 Result
The implementation and evaluation of the proposed system demonstrate its effectiveness in accurately classifying mental health disorders using EEG signal images. The system achieves high performance across multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The results indicate that the hybrid model outperforms conventional EEG-based classification methods, particularly in distinguishing between closely related neurological conditions.

The preprocessing stage successfully removes noise and artifacts from raw EEG signals, ensuring high-quality input data. The spectrogram generation process effectively captures time-frequency information, providing a rich representation of brain activity. The

ESRGAN-based enhancement further improves image quality, allowing the model to detect subtle patterns that are critical for classification.

The DT demonstrates strong capability in extracting meaningful features from enhanced images, while the decision tree classifier provides clear and interpretable classification results. The system shows consistent performance across different datasets, highlighting its robustness and reliability.

The experimental results confirm that the proposed framework can accurately identify Stress and depression, making it a valuable tool for early diagnosis. The automated nature of the system reduces dependency on manual analysis and enables faster decision-making in clinical environments.

9.2 Future Enhancements

Although the proposed system demonstrates strong performance, there are several opportunities for further improvement and expansion. One potential enhancement is the integration of larger and more diverse EEG datasets, which would improve the generalization capability of the model and make it more applicable to different populations and clinical conditions. Another area for improvement is the incorporation of advanced deep learning architectures such as transformer-based models or attention mechanisms. These techniques can further enhance feature extraction and improve classification accuracy by capturing long-range dependencies in EEG data. The system can also be extended to support additional mental health disorders beyond Stress and depression. This would increase its applicability in broader healthcare scenarios and make it a more comprehensive diagnostic tool. Real-time implementation is another important direction for future work. By integrating the system with wearable EEG devices and cloud-based platforms, it can be used for continuous monitoring and early detection in real-world environments.

Furthermore, the inclusion of explainable artificial intelligence techniques can improve transparency and trust in the system. Providing detailed explanations for classification results will help clinicians better understand the decision-making process.

Finally, the system can be integrated with multimodal data sources such as speech, facial expressions, and physiological signals to enhance diagnostic accuracy. Combining multiple data modalities will provide a more holistic understanding of mental health conditions and lead to more effective treatment strategies.

In conclusion, the proposed system lays a strong foundation for future research and development in intelligent mental health diagnostics. With continued advancements and enhancements, it has the potential to become a highly effective tool in modern healthcare systems.

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