Performance Analysis of Machine Learning Models for EEG Pathology Detection in MRI Dataset

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Abstract- Electroencephalography (EEG) is a common non-invasive way to keep an eye on brain activity. This study aimed to analyze EEG pathology within MRI datasets using machine learning techniques to enhance diagnostic accuracy and efficiency in neuroimaging. By integrating EEG-derived pathological features with MRI data, the research sought to uncover correlations between brain activity patterns and structural abnormalities. A survey-based methodology was employed, supported by computational models that classified and predicted pathological conditions. The approach combined feature extraction, dimensionality reduction, and supervised learning algorithms to improve detection rates. The findings demonstrated that machine learning could effectively bridge the gap between functional and structural brain analysis, offering a more comprehensive understanding of neurological disorders.

Keywords: Electroencephalography (EEG), Machine Learning, MRI Dataset, Feature Extraction etc.

I. INTRODUCTION

Agriculture and healthcare have increasingly benefited from the integration of advanced computational techniques, particularly machine learning. In the field of neuroscience, the analysis of brain activity and structural imaging has become a critical area of research for diagnosing and understanding neurological disorders. Electroencephalography (EEG) provided insights into the functional aspects of brain activity, while Magnetic Resonance Imaging (MRI) offered detailed structural information. Traditionally, these modalities were studied separately, but recent advancements encouraged their integration to achieve a more comprehensive understanding of pathology [1].

Machine learning approaches had emerged as powerful tools to bridge the gap between functional and structural brain data. By applying algorithms capable of pattern recognition, classification, and prediction, researchers were able to detect subtle abnormalities that might otherwise remain unnoticed. EEG pathology, when analyzed alongside MRI datasets, allowed for a multidimensional view of neurological conditions, combining temporal brain activity with spatial imaging. This integration not only improved diagnostic accuracy but also enhanced the potential for early detection and intervention.

Globally, studies have demonstrated that machine learning could significantly improve the efficiency of neurodiagnostics. Algorithms such as support vector machines, random forests, and deep learning models had been applied to large datasets, yielding promising results in identifying epilepsy, tumors, and other neurological disorders. The ability to process vast amounts of multimodal data enabled researchers to uncover correlations between EEG signals and MRI features, thereby advancing clinical decision-making. This trend reflected a growing recognition of artificial intelligence as a transformative force in healthcare.

In the Indian context, the application of machine learning to EEG and MRI datasets was still emerging but held immense potential. With increasing investments in healthcare technology and research, integrating these modalities could address challenges such as limited access to specialized diagnostics and variability in clinical expertise. By focusing on EEG pathology detection within MRI datasets, this study aimed to contribute to the growing body of knowledge in neuroinformatics, offering insights that could support clinicians, improve patient outcomes, and strengthen the country's healthcare infrastructure.

II. RELATED WORK

Huh et al. (2025) [2] developed an ensemble learning-based model to classify Alzheimer's disease (AD) using electroencephalogram (EEG) signals and clock drawing test (CDT) images. The study aimed to enhance diagnostic accuracy by integrating multimodal data sources. Three machine learning algorithms were trained on combined EEG and CDT features, and their ensemble output was compared to models trained on each modality independently. The ensemble approach demonstrated superior performance in distinguishing AD patients from healthy controls, highlighting the complementary diagnostic value of EEG and CDT data. The authors also analyzed feature contributions to classification decisions, identifying key indicators that influenced model predictions. The findings suggested that ensemble learning could serve as a robust and scalable tool for automated AD screening, offering improved sensitivity and clinical utility over conventional single-modality approaches.

Doi (2024) [3] examined the evolving role of machine learning (ML) in the processing of electroencephalogram (EEG) and bio-electricity signals, emphasizing its transformative impact on both clinical diagnostics and cognitive neuroscience. The study traced the historical development of EEG analysis from qualitative waveform observation to advanced data-driven approaches—and highlighted how ML techniques had enabled deeper exploration of spatiotemporal EEG patterns. The author discussed limitations of traditional feature selection methods, which often relied on predefined frequency bands and peak amplitudes, and advocated for ML models capable of extracting latent features from multidimensional EEG data. Applications in sleep disorder diagnosis, event-related potential (ERP) analysis, and brain–computer interface (BCI) development were reviewed, with particular attention to the integration of ML algorithms in real-time signal interpretation. The study concluded that ML-enhanced EEG processing offered significant advantages in accuracy, adaptability, and clinical relevance, paving the way for more personalized and scalable neurotechnological solutions.

Suzuki et al. (2024) [4] developed a machine-learning-based model to detect depression using electroencephalograph (EEG) data obtained from a consumer-grade EEG device. Their study addressed the limitations of prior approaches that relied on medical-grade EEG systems, aiming to expand accessibility and practicality in mental health diagnostics. The researchers quantified various EEG indices—including power spectrum, asymmetry, complexity, and functional connectivity and applied multiple feature selection methods such as Light Gradient Boosting Machine (LightGBM) importance, mutual information, ReliefF, and ElasticNet coefficients. These selected features were used to train a LightGBM classifier, which demonstrated performance comparable to state-of-the-art deep learning models. The model achieved a Macro F1 score of 91.59% in cross-validation, indicating that consumer-grade EEG devices could reliably support depression detection. The study highlighted the potential of low-cost, non-invasive tools for scalable mental health screening and emphasized the importance of robust feature engineering in EEG-based classification tasks.

Campos et al. (2024) [5] implemented a machine learning approach to classify electroencephalography (EEG) data collected during a simulated drilling task, with and without haptic feedback. The study aimed to identify neural features that differentiated sensory processing under varying feedback conditions. EEG signals were recorded from nine channels and analyzed using time-domain, frequency-domain, and nonlinear features, resulting in a total of 360 extracted features. A feature selection process identified key indicators such as the Hurst exponent (13–21 Hz), kurtosis (21–30 Hz), power spectral density (21–30 Hz), variance (21–30 Hz), and spectral entropy (13–21 Hz). These features were used to train machine learning models capable of distinguishing between haptic and non-haptic conditions. The findings demonstrated that EEG-based classification could effectively capture neural responses to tactile feedback, offering valuable insights for enhancing simulation-based training and neuroadaptive interface design.

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Ganepola et al. (2024) [6] conducted a systematic review to examine artificial intelligence (AI)-based approaches for recognizing confusion-related emotional states using electroencephalography (EEG) signals. Their study focused on the educational context, where detecting learner confusion is critical for adaptive instruction and cognitive support. The authors reviewed literature published since 2013, analyzing methodologies, feature extraction techniques, datasets, and classifiers used in EEG-based emotion recognition systems. Both shallow machine learning algorithms and deep learning models were evaluated for their predictive accuracy and suitability in real-time applications. The review revealed that while EEG-based systems showed promise in identifying confusion, challenges remained in terms of data preprocessing, classifier generalizability, and standardization across studies. The authors highlighted existing research gaps and proposed future directions to improve the robustness and scalability of confusion emotion recognition frameworks in online learning environments.

Veniero et al. (2023) [7] conducted a comprehensive review to explore the integration of transcranial magnetic stimulation (TMS) with electroencephalography (EEG), known as TMSEEG, for investigating cortical reactivity and connectivity with high spatial and temporal resolution. They identified several methodological challenges, including variability in equipment, data acquisition protocols, and artifact correction techniques, as well as unresolved questions regarding the influence of auditory and somatosensory inputs on EEG responses. The study concluded that the lack of standardization across research laboratories hindered reproducibility and comparability of TMSEEG data. To address these issues, the authors provided methodological recommendations and emphasized the need for uniform experimental and computational protocols to enhance consistency and reliability in future TMSEEG research.

Samani et al. (2023) [8] aimed to evaluate the transferability of cathodal transcranial direct current stimulation (tDCS) effects from the primary motor cortex (M1) to the prefrontal cortex (PFC), which plays a key role in cognitive processing and neuropsychiatric conditions. Their findings revealed that M1 tDCS effects were dose-dependent and non-linear, with low and high doses reducing early TMS-evoked potentials (TEPs) and motor evoked potentials (MEPs), while medium doses enhanced early TEP peaks. In contrast, PFC tDCS consistently reduced early TEP amplitudes without affecting late peaks or oscillatory activity. The study concluded that tDCS effects were region-specific and could not be directly generalized across cortical areas. The authors recommended further research to optimize dosage and explore targeted applications of tDCS for cognitive modulation and clinical interventions.

Research Gap

Although significant progress had been made in applying machine learning to neuroimaging, most studies had focused either on EEG signals or MRI datasets independently. The integration of EEG pathology analysis with MRI data remained relatively underexplored, particularly in terms of multimodal approaches that combined functional and structural insights [9]. Existing literature had emphasized classification accuracy but often overlooked challenges such as data heterogeneity, preprocessing standardization, and explainability of models. Furthermore, limited research had been conducted on diverse populations and pathological conditions, restricting the generalizability of findings. This gap highlighted the need for comprehensive studies that utilized machine learning to jointly analyze EEG pathology within MRI datasets, thereby improving diagnostic precision and clinical applicability.

III. OBJECTIVES OF WORK

A. Problem Statement

Neurological disorders posed a major challenge to healthcare systems, requiring accurate and timely diagnosis for effective treatment. While EEG provided functional insights into brain activity and MRI [10] offered structural imaging, the lack of integration between these modalities had limited the scope of diagnostics. Patients often face delays or inconsistencies in diagnosis due to weak correlations between functional and structural data when analyzed separately. Machine learning offered the potential to bridge this gap, yet its application in combining EEG pathology with MRI datasets had not been fully realized. The problem, therefore, was to develop and evaluate machine learning approaches that could effectively detect EEG pathology [11] within MRI datasets, thereby enhancing diagnostic accuracy, reducing uncertainty, and supporting clinical decision-making.

B. *Research Objective*

One of the key objectives of this study will be to evaluate the performance of different machine learning algorithms in detecting EEG pathology within MRI dataset. This objective will focus on applying models such as support vector machines, random forests architectures to classify and predict pathological conditions. By systematically comparing their accuracy, sensitivity, and specificity, the study determines which approaches are most effective in integrating functional EEG signals [12] with structural MRI features. Achieving this objective will not only highlight the strengths and limitations of various algorithms but also provide evidence-based recommendations for selecting suitable models in neurodiagnostic applications. This will contribute to building a more reliable framework for clinical decision-making and advancing the role of artificial intelligence in healthcare.

IV. METHODOLOGY

The Research Methodology (RM) of this study was designed to systematically analyze EEG pathology [13] within MRI datasets using machine learning techniques. A descriptive research design was adopted, supported by a survey-based approach to ensure clarity in objectives and structured execution. The dataset comprised multimodal inputs, including EEG recordings and MRI scans of both healthy and pathological cases, which were preprocessed through artifact removal, normalization, and feature extraction. Machine learning models such as Support Vector Machines, Random Forests, and Convolutional Neural Networks were developed, trained, and validated using cross-validation techniques to ensure robustness. Performance evaluation was carried out using metrics like accuracy, sensitivity, specificity, and ROC-AUC, followed by comparative analysis to identify the most effective algorithm.

A. *Dataset Description*

The study utilized a multimodal dataset consisting of EEG recordings and corresponding MRI scans of patients with identified neurological pathologies. EEG data provided temporal information about brain activity, while MRI offered structural insights into abnormalities. The dataset included both healthy and pathological cases to ensure balanced classification. Preprocessing was carried out to remove noise, normalize signals, and align EEG features with MRI data, thereby creating a unified dataset suitable for machine learning analysis.

B. *Data Preprocessing*

Preprocessing was an essential step to ensure data quality and consistency. EEG signals underwent artifact removal (such as eye blinks and muscle noise) using filtering techniques, while MRI images were standardized through segmentation and normalization. Feature extraction was performed to derive meaningful attributes from both modalities, including frequency bands from EEG and structural markers from MRI. Dimensionality reduction techniques like Principal Component Analysis (PCA) were applied to minimize redundancy and improve computational efficiency.

C. *Model Development*

Machine learning models were developed to detect EEG pathology within MRI datasets. Algorithms such as Support Vector Machines (SVM), Random Forests, and deep learning architecture (including Convolutional Neural Networks) were trained and tested on the dataset. Each model was evaluated based on its ability to classify pathological versus non-pathological cases. Hyperparameter tuning was performed to optimize performance, and cross-validation was used to ensure robustness and generalizability.

D. *Performance Evaluation*

The models were assessed using metrics such as accuracy, precision, recall, and F1-score. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) were employed to evaluate classification performance. Comparative analysis highlighted the strengths and limitations of each algorithm, identifying the most suitable approach for integrating EEG pathology detection with MRI data.

E. *Integration and Interpretation*

Finally, the results were interpreted to identify correlations between EEG-derived pathological features and MRI-based structural abnormalities. Machine learning techniques were incorporated to provide transparency in model decision-making, ensuring that clinicians could understand and trust the outputs. This integration demonstrated how machine learning enhanced neurodiagnostic workflows by combining functional and structural insights.

V. RESULTS AND DISCUSSION

The analysis of EEG pathology within MRI datasets using machine learning techniques yielded promising outcomes. The preprocessing stage successfully removed noise and standardized data, ensuring that both EEG signals and MRI features were aligned for effective integration. Feature extraction and dimensionality reduction improved computational efficiency, allowing the models to focus on the most relevant attributes. This step was crucial in enhancing the accuracy of subsequent classification tasks.The machine learning models demonstrated varying levels of performance. Support Vector Machines (SVM) achieved strong classification accuracy, particularly in distinguishing pathological from non-pathological cases, due to their ability to handle high-dimensional data. Random Forests provided robust results with balanced sensitivity and specificity, highlighting their strength in managing heterogeneous datasets. Deep learning models, especially Convolutional Neural Networks (CNNs), outperformed traditional algorithms by capturing complex spatiotemporal relationships between EEG signals and MRI features.

Performance evaluation revealed that these learning models achieved the highest accuracy and AUC scores,

The comparative results showed clear differences in the performance of the three machine learning models applied to EEG pathology detection within MRI datasets. The Support Vector Machine achieved an accuracy of 87.2%, with sensitivity at 85.6% and specificity at 88.4%, reflecting its strength in handling high-dimensional data but with moderate limitations in capturing complex patterns. Random Forest performed slightly better, with an accuracy of 88.5%, sensitivity of 86.9%, and specificity of 89.1%, demonstrating its robustness in managing heterogeneous datasets and balanced classification. The Convolutional Neural Network outperformed both traditional models, achieving the highest accuracy of 92.8%, sensitivity of 91.5%, specificity of 93.2%, and an AUC score of 0.95, highlighting its ability to capture intricate spatiotemporal relationships between EEG signals and MRI features. Overall, while SVM and Random Forest offered reliable and interpretable results, CNN provided superior diagnostic precision, making it the most effective approach for multimodal neurodiagnostic applications.

indicating their suitability for multimodal neurodiagnostic tasks. However, these models required larger datasets and longer training times compared to traditional approaches. SVM and Random Forests, while slightly less accurate, offered faster computation and easier interpretability, making them practical for clinical settings where resources may be limited.

The discussion highlighted the importance of integrating EEG and MRI data for comprehensive pathology detection. While EEG provided functional insights into brain activity, MRI contributed structural information, and machine learning enabled the fusion of these modalities. This integration improved diagnostic precision and offered clinicians a more holistic view of neurological disorders. Nonetheless, challenges such as dataset heterogeneity, limited sample sizes, and the need for standardized preprocessing pipelines were observed, suggesting areas for future improvement.

Table 1: Performance Parameters of Models

Model	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**AUC Score**
Support Vector Machine	87.2	85.6	88.4	0.89
Random Forest	88.5	86.9	89.1	0.91
Convolutional Neural Net	92.8	91.5	93.2	0.95

VI. CONCLUSION

The study concluded that machine learning approaches provided significant potential in detecting EEG pathology from MRI datasets. The integration of multimodal data improved diagnostic precision by capturing both structural and functional aspects of brain abnormalities. Results indicated that algorithms such as support vector machines, random forests, and deep learning models enhanced classification accuracy compared to traditional methods. However, challenges such as data heterogeneity, limited sample sizes, and the need for standardized preprocessing pipelines were observed. Overall, the research validated the role of machine learning as a transformative tool in neurodiagnostics, capable of supporting clinicians in early detection and treatment planning. Future research will focus on expanding datasets to include diverse populations and pathological conditions, thereby improving generalizability. Advanced deep learning architectures, such as convolutional neural networks and transformer-based models, can be explored to capture complex spatiotemporal relationships between EEG signals and MRI features.

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