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COMPARATIVE ANALYSIS OF BRAIN ACTIVITY CLASSIFICATION USING CONVOLUTION NEURAL NETWORKS

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Abstract

Electroencephalograms (EEGs) play a crucial role in detecting harmful brain activity by capturing electrical signals from the brain. This study aims to develop a deep learning framework for classifying EEG images into their respective brain activity categories. To achieve this, raw EEG signals were first converted into spectrograms, which provide a visual representation of signal frequencies over time. These spectrograms were then processed using pre-trained deep learning models to determine the most effective model for accurate classification. The dataset used for training and evaluation consists of EEG recordings categorized into six distinct brain activity labels. The deep learning models implemented for this classification task include VGG16, AlexNet, ResNet, and InceptionV3. The models were trained using a comprehensive dataset, and their performance was assessed using standard evaluation metrics. After extensive experimentation and comparison, the results indicate that InceptionV3 outperforms the other models in classifying EEG spectrograms. Its superior performance can be attributed to its advanced architecture, which effectively captures complex patterns within the spectrogram data. These findings highlight the potential of deep learning in analyzing EEG signals and classifying harmful brain activities with high accuracy. Future research could explore further improvements by incorporating more advanced neural architectures, such as Vision Transformers or custom-built CNN models, to enhance classification performance beyond what pre-trained models can achieve.

***Keywords*:**
Anomaly Detection; EEG classification; Deep Learning; Convolution Neural Networks

1. INTRODUCTION

The classification of harmful brain activity using machine learning and deep learning represents a crucial advancement in neuroscience, with significant implications for diagnosing, treating, and managing neurological disorders. By employing sophisticated computational techniques to analyze complex brain signals, researchers aim to develop precise and efficient tools for detecting and categorizing abnormal neural activity linked to conditions such as epilepsy, Alzheimer's disease, Parkinson's disease, and traumatic brain injury.

Electroencephalography (EEG) is a primary modality used to study brain activity, capturing electrical signals through electrodes placed on the scalp. As a non-invasive and cost-effective method, EEG enables real-time monitoring of brain function. Deep learning models including CNNs and RNNs, have demonstrated significant potential in identifying abnormal EEG patterns, particularly in epileptic seizure detection. These models automatically learn meaningful features from raw EEG data, leading to improved seizure prediction and classification accuracy.

Beyond scalp EEG, intra-cranial EEG (iEEG) offers higher spatial resolution by placing electrodes directly on the brain's surface or within neural tissue. Deep learning approaches applied to iEEG data have been instrumental in localizing epileptogenic zones and aiding surgical interventions for patients with drug-resistant epilepsy. By analyzing spatiotemporal patterns within iEEG recordings, these models assist clinicians in pinpointing abnormal brain activity regions responsible for seizures.

Machine learning and deep learning methodologies extend beyond EEG and iEEG to other neuroimaging techniques such as fMRI, PET, and MEG. These modalities provide complementary insights into brain structure, function, and metabolism, facilitating the diagnosis and characterization of various neurological disorders. For instance, deep learning models trained on fMRI data have been used to differentiate between Alzheimer's disease patients and healthy individuals based on patterns of brain connectivity and activity.

Additionally, machine learning algorithms play a crucial role in analyzing multimodal data fusion, where information from multiple imaging techniques or biological markers is combined to enhance diagnostic accuracy and prognostic prediction. Integrating EEG, fMRI, and genetic data can lead to a deeper understanding of neurological disorders and support personalized treatment strategies tailored to individual patient needs.

Despite these advancements, several challenges persist in harmful brain activity classification. Issues such as data heterogeneity, small sample sizes, and variability among patient populations pose hurdles to developing robust and generalizable models. Moreover, ensuring model interpretability and clinical applicability remains essential for translating research findings into effective medical practice.

This paper is structured as follows: Section 1 introduces machine learning applications in neuroimaging, Section 2 reviews prior research on EEG-based classification, Section 3 outlines the methodology and algorithms employed, Section 4 presents experimental results and analysis, and Section 5 concludes with future research directions.

2. LITERATURE REVIEW

EEG classification has received considerable attention in neuroscience research, particularly for applications such as brain-computer interfaces (BCIs), epileptic seizure detection, and cognitive state estimation. Several influential studies have significantly contributed to advancing EEG data analysis and classification methodologies.

In neuroimaging, the searchlight algorithm [1] is a widely used multivariate pattern analysis (MVPA) technique that helps identify localized brain regions associated with specific cognitive or behavioral tasks. This method systematically scans small, overlapping clusters of voxels (3D pixels) across the brain, applying classification or decoding techniques to determine whether neural activity within each cluster differentiates between experimental conditions. The accuracy results are mapped across the brain, revealing regions where neural patterns are most informative. This approach enables a fine-grained, data-driven exploration of brain-behavior relationships without requiring prior assumptions about relevant brain areas.

A comprehensive review by [2] discusses deep learning applications in EEG and magnetoencephalography (MEG) data analysis. The authors examine various deep learning architectures, datasets, and challenges in utilizing deep learning for EEG and MEG classification tasks. Another review by [3] specifically explores the use of deep learning techniques for classifying motor imagery tasks based on EEG signals, addressing different architectures, preprocessing methods, and classification challenges.

Acharya et al. [4] pioneered an early method for automated epileptic seizure detection using EEG signals. Their approach involved extracting features based on line length and employing artificial neural networks (ANNs) for classification, demonstrating promising results. In a subsequent study, Acharya et al. [5] proposed an entropy-based feature extraction method for epileptic EEG classification, using machine learning models such as support vector machines (SVMs) and ANNs.

Lawhern et al. [6] introduced EEGNet, a compact convolutional neural network (CNN) architecture specifically designed for EEG-based BCIs. EEGNet achieved state-of-the-art performance on several benchmark datasets, particularly for motor imagery and P300 speller tasks. In another study, Dahshan et al. [7] investigated deep learning techniques for epileptic seizure prediction using EEG data, developing a CNN architecture and evaluating various preprocessing strategies and network configurations.

These key studies underscore the importance of machine learning and deep learning in EEG classification research, contributing to advances in BCIs, epileptic seizure detection, and clinical decision support systems for neurological disorders. Several high-level frameworks streamline the application of machine learning to neuroimaging. PyMVPA [8], a Python-based package, supports multivariate pattern analysis while integrating with external tools such as R, scikit-learn, and Shogun [9]. PRoNTo [10], developed in Matlab, interfaces with SPM but provides a limited selection of machine learning algorithms.

Before applying statistical learning to neuroimaging data, standard preprocessing steps are necessary. For fMRI, preprocessing typically involves motion correction, slice timing correction, co-registration with an anatomical image, and normalization to a common template such as the Montreal Neurological Institute (MNI) space. Widely used tools for these processes include SPM [11] and FSL [12], with a Python interface available through the nipype library [13].

In [14], the authors collected raw EEG signals using an Emotiv Epoc+ X 14-channel headset and, after outlier detection, reduced the dataset to 62,286 rows and 86 columns. They trained four machine learning models—kNN, SVM, decision trees, and random forest—on the dataset, finding that the SVM model achieved the best performance.

3. METHODOLOGY

Brain waves are electrical signals in the brain that vary over time and are measured in volts. These waves are categorized into five primary types based on their frequency ranges. Gamma (γ) waves, exceeding 35Hz, are associated with heightened cognitive activity and intense focus. Beta (β) waves, spanning 12Hz to 35Hz, are linked to alertness and anxiety. Alpha (α) waves, ranging from 8Hz to 12Hz, indicate a relaxed but awake state. Theta (θ) waves, occurring between 4Hz and 8Hz, are connected to deep relaxation and light sleep. Lastly, Delta (δ) waves, with frequencies from 0Hz to 4Hz, are predominant during deep sleep.

Electroencephalography (EEG) data consists of multiple channels, each capturing brain wave activity from different regions of the brain. Typically, EEG data is formatted as a multi-channel time series that requires preprocessing before analysis. One useful technique for visualizing frequency changes over time is the spectrogram, which represents how signal frequencies evolve. A spectrogram is generated using the Short-Time Fourier Transform (STFT), which segments the signal into overlapping windows and applies the Fourier transform to each, revealing frequency content over time.

To extract meaningful features from EEG data, spectrograms can be derived from EEG signals. Standardizing these spectrograms ensures consistency in their dimensions before processing them through deep learning models. Various deep learning architectures, including AlexNet, VGG-16, ResNet, and InceptionV3, are applied to the preprocessed spectrograms to classify brain wave patterns. Model performance is evaluated to determine the most effective approach for EEG signal analysis (Figure-1).

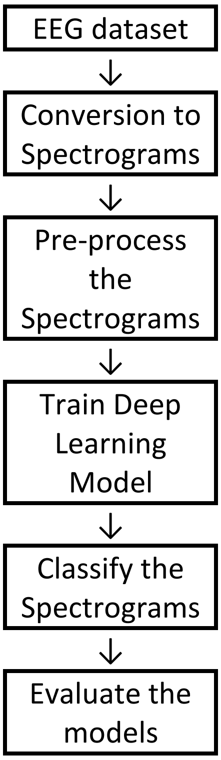


Fig.1. Methodology

AlexNet [15] was one of the first convolutional neural networks (CNNs) to revolutionize computer vision. It won the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC), significantly surpassing previous approaches. The architecture consists of five convolutional layers followed by three fully connected layers, incorporating ReLU activations and max-pooling layers. AlexNet introduced key innovations, such as extensive use of dropout to mitigate overfitting and the ReLU activation function, which accelerated training.

The Visual Geometry Group (VGG) at the University of Oxford developed VGG16 and VGG19 [16] as part of their deep learning research. These models follow a simple yet effective architectural design, consisting of only 3×3 convolutional layers and 2×2 max-pooling layers. VGG16 includes 13 convolutional layers and three fully connected layers, while VGG19 extends this with additional convolutional layers. Despite their straightforward structure, VGG networks achieve outstanding performance in various computer vision tasks and serve as benchmark architectures. However, their deep layer stack, while beneficial for feature extraction, makes them computationally intensive compared to shallower networks like AlexNet.

ResNet [17] introduced "residual learning," where the network learns the difference between input and output rather than mapping the function directly. This is achieved through shortcut connections (also called skip connections or identity mappings), which allow gradients to propagate more effectively during backpropagation, addressing the vanishing gradient problem. The architecture is built upon residual blocks, which include identity blocks, where the shortcut connection passes input directly to the output if dimensions remain unchanged, and convolutional blocks, which use 1×1 convolutions to match input and output dimensions. ResNet architectures are categorized by layer depth, including ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. Deeper versions, such as ResNet-50 and beyond, incorporate bottleneck blocks, which use 1×1, 3×3, and another 1×1 convolution to reduce computational cost while preserving representational power.

GoogleNet [18], also known as Inception V1, was developed by Google researchers as part of the GoogLeNet project. Its key innovation is the Inception module, which integrates multiple convolutional layers with different filter sizes operating in parallel. This design allows the network to capture multi-scale features while maintaining computational efficiency. The Inception module comprises four parallel paths: 1×1 convolutions for fine-grained features, 3×3 convolutions for medium-sized features, 5×5 convolutions for capturing larger features, and max-pooling to retain spatial information. To optimize efficiency, 1×1 convolutions are used for dimensionality reduction before applying larger filters. Additionally, auxiliary classifiers attached to intermediate layers serve as a form of regularization, preventing the vanishing gradient problem during training. While these auxiliary classifiers are discarded during inference, they enhance the model's training stability.

DenseNet [19] (Dense Convolutional Network), developed by Facebook AI Research (FAIR), introduces dense connections, where each layer is connected to all subsequent layers within a dense block. This design promotes feature reuse, enhances gradient flow, and mitigates the vanishing gradient problem. Due to its efficient parameter sharing, DenseNet delivers strong performance on various image classification tasks while requiring fewer parameters compared to traditional deep networks.

EfficientNet [20] introduces a novel method that uniformly adjusts the network’s depth, width, and resolution. These coefficients, denoted as phi (ϕ), control the network’s size across different dimensions. By scaling all dimensions simultaneously, EfficientNet achieves superior performance compared to traditional scaling methods while maintaining computational efficiency. The architecture is built upon a baseline model, EfficientNet-B0, which is designed for optimal accuracy while remaining computationally efficient. Its structure consists of a backbone network composed of repeated blocks, similar to architectures like ResNet. Each block includes a series of convolutional layers followed by batch normalization and activation functions such as Swish or ReLU. EfficientNet employs compound scaling to systematically expand the network’s depth, width, and resolution, ensuring balanced growth across all dimensions. A key innovation in EfficientNet is the introduction of the "MBConv" block (Mobile Inverted Residual Bottleneck Convolutional), inspired by MobileNetV2. The MBConv block utilizes depth-wise separable convolutions followed by squeeze-and-excitation (SE) blocks, which dynamically recalibrate channel-wise feature responses. This design enhances feature representation while keeping the model compact and computationally efficient. EfficientNet offers multiple model variants, ranging from EfficientNet-B0 to EfficientNet-B7, each utilizing different scaling coefficients to balance model size and performance. Smaller variants, such as EfficientNet-B0, are well-suited for resource-constrained environments, while larger models, like EfficientNet-B7, deliver state-of-the-art performance on large-scale datasets.

InceptionV3 [21] builds upon earlier Inception architectures, introducing several optimizations for large-scale image classification. Factorized convolutions replace large filters with smaller ones, reducing computational complexity. Auxiliary classifiers assist in training by improving gradient propagation, helping deeper networks converge effectively. Batch normalization is applied across all layers, stabilizing training and accelerating convergence. Label smoothing regularizes predictions to prevent overconfidence, improving generalization. Efficient grid size reduction techniques replace pooling operations with carefully designed convolutions to preserve feature integrity during downsampling. InceptionV3 is widely used in transfer learning, allowing pre-trained weights from datasets like ImageNet to be fine-tuned for applications such as medical imaging, object detection, and facial recognition. The model's balance between accuracy and computational efficiency makes it suitable for both high-end GPUs and optimized edge devices. Despite the rise of newer architectures like EfficientNet and Vision Transformers, InceptionV3 remains a foundational model in computer vision, influencing subsequent deep learning advancements. Its efficient design and robust feature extraction capabilities ensure its continued relevance across diverse AI applications, from medical diagnostics to industrial automation.

4. EXPERIMENTS & RESULTS

The dataset used in the experiments is the Harmful Brain Activity Classification dataset, sourced from Kaggle. It comprises 17,300 EEG recordings and 11,138 spectrograms, all stored in parquet format. Additionally, a CSV file is provided containing metadata, specifying that each EEG must be classified into one of the following categories (Figure-2): seizure, lateralized periodic discharges (LPD), generalized periodic discharges (GPD), lateralized rhythmic delta activity (LRDA), generalized rhythmic delta activity (GRDA), or other. Several CNN architectures were implemented using the PyTorch library, and their performance was evaluated.

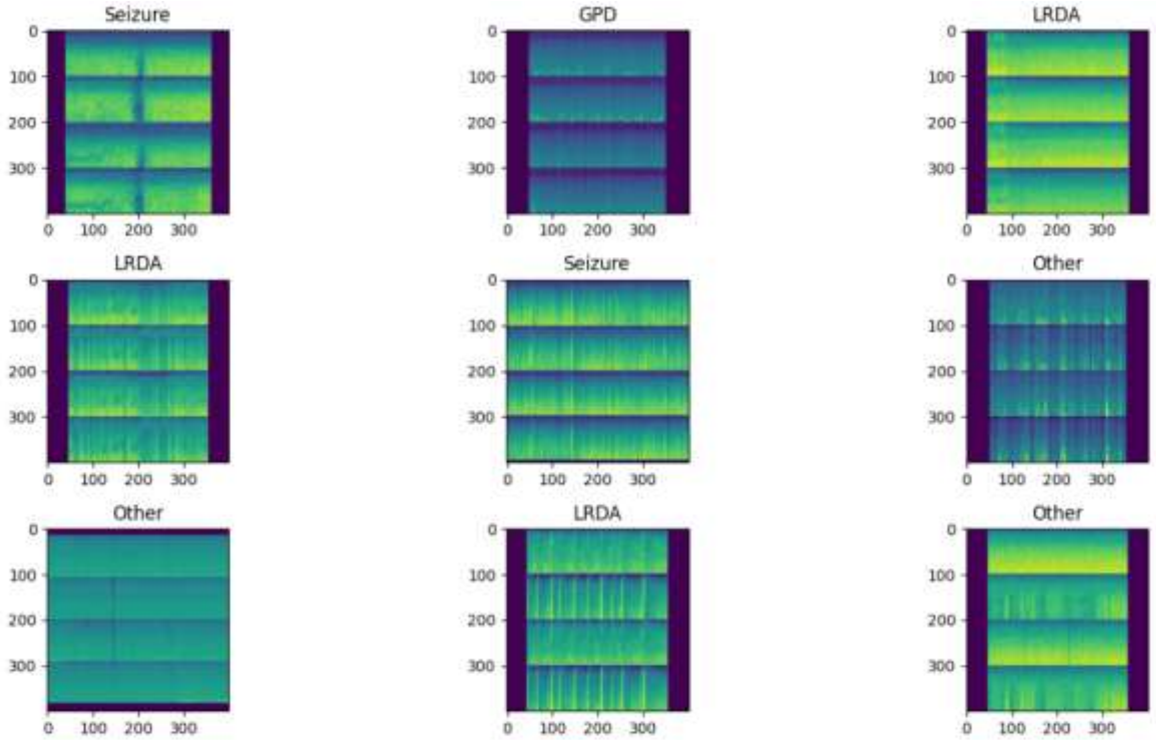
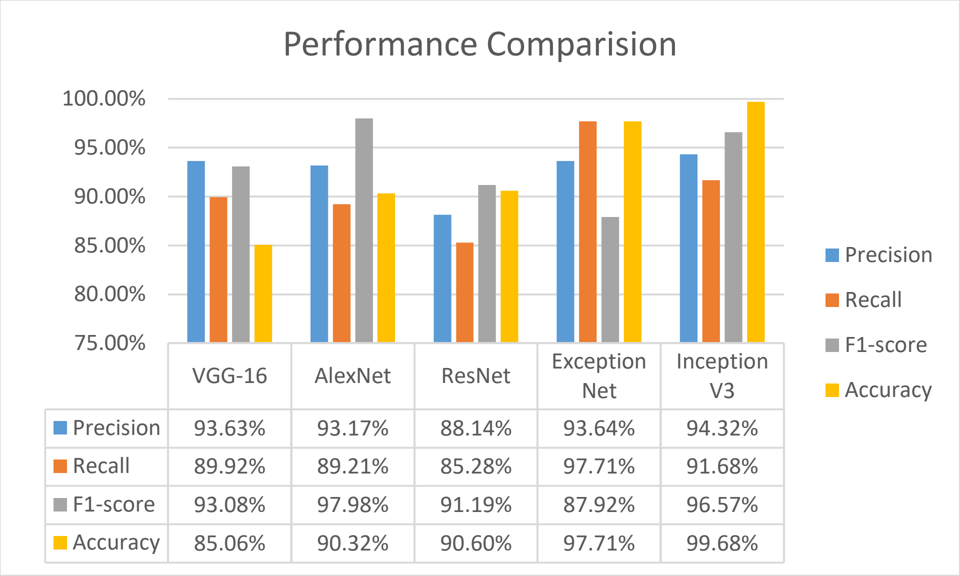


Fig.2. Spectrograms for different brain activities

The various evaluation metrics used to evaluate results are as follows:

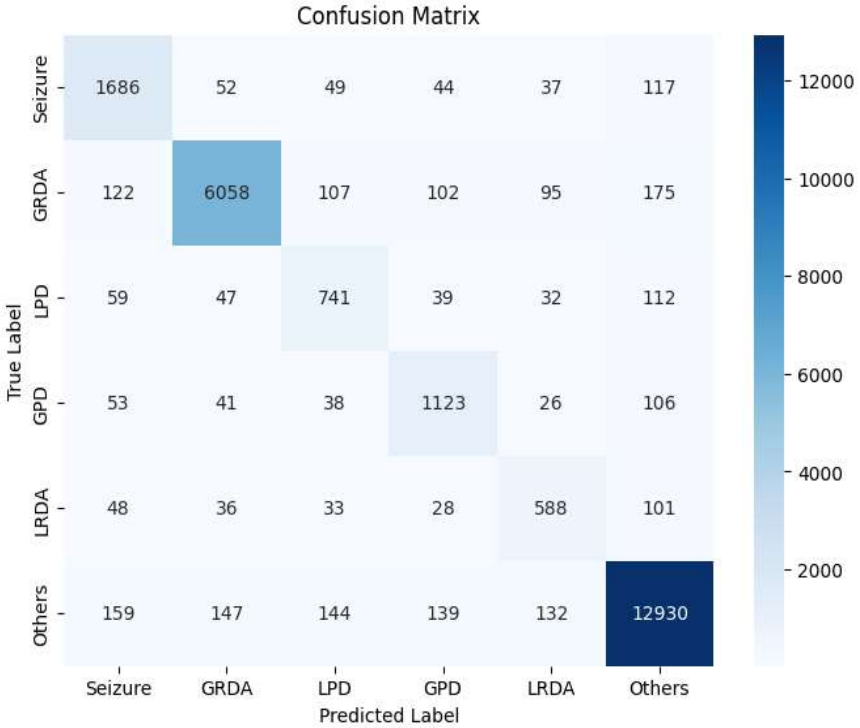
- Accuracy: One of the simplest metrics, accuracy measures the fraction of correctly classified points out of the total points. It's appropriate for balanced datasets but can be deceptive when classes are imbalanced.
  $$Acc = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$
- Precision: Precision measures the fraction of correct positive predictions out of all positive predictions. It's a good metric when the cost of false positives is high.
  $$Precision = \frac{TP}{TP+FP} \quad (2)$$
- Recall (Sensitivity): Recall measures the fraction of correct positive predictions out of all actual positives. It's useful when the cost of false negatives is high.
  $$Recall = \frac{TP}{TP+FN} \quad (3)$$
- F1 Score: It is most appropriate to use when there's an imbalance between classes.
  $$F1\ score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$



	VGG-16	AlexNet	ResNet	Exception Net	Inception V3
Precision	93.63%	93.17%	88.14%	93.64%	94.32%
Recall	89.92%	89.21%	85.28%	97.71%	91.68%
F1-score	93.08%	97.98%	91.19%	87.92%	96.57%
Accuracy	85.06%	90.32%	90.60%	97.71%	99.68%

Fig.3. Performance comparison of different models

From Figure-3, we can infer that InceptionV3 gives the best result compared to VGG-16, AlexNet, and ResNet in terms of all the evaluation metrics. Figure-4 below is the confusion matrix for InceptionV3 on the dataset.



	Seizure	GRDA	LPD	GPD	LRDA	Others
Seizure	1686	52	49	44	37	117
GRDA	122	6058	107	102	95	175
LPD	59	47	741	39	32	112
GPD	53	41	38	1123	26	106
LRDA	48	36	33	28	588	101
Others	159	147	144	139	132	12930

Fig.4. Confusion Matrix (InceptionV3)

5. CONCLUSION & FUTURE SCOPE

This study demonstrates the effectiveness of deep learning models in classifying EEG spectrograms to detect harmful brain activity. By converting EEG signals into spectrograms and utilizing pre-trained CNN architectures, we were able to identify the most suitable model for accurate classification. Among the models evaluated, InceptionV3 exhibited the highest performance across multiple evaluation metrics, highlighting its capability to extract meaningful features from EEG spectrograms. These findings reinforce the potential of deep learning in medical diagnostics, particularly in the analysis of brain activity, and pave the way for further advancements in automated EEG classification.

Future research can explore more advanced neural architectures, such as Vision Transformers, which have shown promise in various image classification tasks. Additionally, developing specialized custom CNN models tailored to EEG spectrogram analysis could further enhance classification accuracy and efficiency. Incorporating domain adaptation techniques and transfer learning from larger EEG datasets may also improve model generalization. Furthermore, integrating explainable AI techniques could provide deeper insights into the decision-making process of the models, making them more interpretable for medical professionals. Finally, real-time EEG classification systems can be developed for clinical applications, enabling faster and more reliable detection of harmful brain activity in real-world scenarios.

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