

Spectrogram-Based EEG brain Signal Classification Using Convolutional Neural Networks

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Abstract

Brain signal which helps in cataloguing has turn out to be a critical fact in the area of research zone in biomedical engineering and artificial intelligence, making it predominant for sleuthing and detecting the neurological disorders in the human brain and also considering and understanding cognitive states. The Electroencephalogram i.e. EEG method is a non-invasive technique which is not painful and used to identify, detect and capture electrical signals as well as activity of the brain with high temporal tenacity features. However, the raw EEG signals are intricate and multifaceted which are non-stationary and complex to interpret or understood directly. This research paper represents an AI-based framework for categorizing the brain signals using EEG spectrogram images. This anticipated approach transforms the EEG time-series signals converted into time–frequency spectrogram depictions and also applies Convolutional Neural Networks (CNNs) for automatic feature extraction of the images and further doing classification. The model is basically assessed using typical performance metrics calculation including accuracy, precision, recall, F1-score and confusion matrix. The experimental discoveries reveal and demonstrate that spectrogram-based image which deep learning meaningfully improvises the classification of the performance compared to traditional or old dated machine learning methodology. This study highlights the potential and benefits of AI-driven EEG report analysis in medical diagnostics, brain and computer interfaces and cognitive reasoning of state monitoring.

Keywords:

EEG signals, CNN techniques, Spectrogram, models, deep learning approach

1. Introduction

The human brain produces electrical signal which impulses and that can be measured and calculated using EEG technology. EEG signals reflect on the neural activity of the human brain and are broadly used for detecting and diagnosing the diseases like epilepsy, sleep syndromes, dementia and other neurological problems as well as conditions. Basically, due to their non-linear and non-stationary nature, the EEG signals are required for progressive computational approaches for expressive interpretation and understanding.

Conventional signal processing techniques depend on manually designed features, including statistical measures, spectral energy concentration, and wavelet-based coefficients. While excellently these approaches only be contingent deeply on domain and field proficiency. Artificial Intelligence (AI) especially in the area of deep learning offers automated feature erudition and improvised cataloguing of images with accuracy maintained.

Convolutional Neural Networks (CNNs) was initially developed for image recognition tasks which was being adapted for EEG analysis by converting brain signals into photographic or visual representations such as spectrograms. A spectrogram is a technique which captures both frequency that is rate of recurrence and progressive information making it more suitable for sleuthing brain activity and its patterns.

2. Background and Literature Review

Electroencephalography (EEG) signals are often understood by distributing them according to frequency ranges such as delta, theta, alpha, beta and gamma each reflecting on different brain functions.

EEG signals are commonly analyzed in following frequency bands range are:

- Delta (0.5–4 Hz)
- Theta (4–8 Hz)
- Alpha (8–13 Hz)
- Beta (13–30 Hz)
- Gamma (>30 Hz)

With the advancement of deep learning models which have recognized highly effective in image classification. By translating EEG data into spectrograms image. Researchers applies CNN techniques to recognize a pattern and supporting applications like Seizure recognition, Affective or emotion state detection and Mental workload assessment which are important applications of EEG signal processing that help in identifying neurological disorders, understanding human emotions and measuring mental effort during different tasks.

Recent advances in deep learning architectures such as:

- VGGNet
- ResNet
- MobileNet

The result has shown strong performance in image-based cataloguing tasks. Compared to traditional classifiers SVM, KNN and Random Forest, CNNs eliminate manual feature engineering by learning hierarchical representations automatically.

3. Methodology

EEG signals are collected and preprocessed to remove noise disturbance and artifacts. The cleansed data is then transformed and made into spectrogram images via time frequency analysis method. These images are then fed into a convolutional neural network for the features extraction and cataloguing. The model is well trained and validated to give accurate result, identifying the patterns conforming to diverse brain statuses or circumstances.

System Overview

The proposed framework consists of:

- a. EEG Signal Procurement
- b. Signal conditioning / Preprocessing
- c. Spectral mapping / Spectrogram Generation
- d. Convolutional Neural Network Classification
- e. Model assessment / Accuracy analysis

a. EEG Data Procurement

EEG signals can be accumulated using multiple channels of EEG devices. The public datasets such as PhysioNet EEG Motor Movement or Imagery Dataset are commonly used for research purposes.

b. Signal conditioning / Preprocessing

Steps include for signal data cleaning are:

- **Band-pass filtering (0.5–45 Hz):** Removing of unwanted frequencies that is outside the EEG range and keeping only germane brain signal mechanisms.
- **Artifact removal (eye blink, muscle noise):** Elimination of noise caused by eye movements and other muscle activity to improvise the quality of signal.
- **Signal standardization:** Scales in which the EEG data to be consistently ranged for furtherance of model performance and assessment.
- **Dissection into fixed-length windows:** Dividing of continuous EEG signs into a smaller and equal segment for easier scrutiny and processing.

c. Spectral mapping / Spectrogram Generation

A spectrogram is engendered using Short-Time Fourier Transform (STFT) technique:

First image shows different stages of **EEG signal processing**:

- **A:** Raw EEG signal over time (noisy brain wave data)
- **B:** Zoomed-in sight of the EEG signal for comprehensive observation
- **C:** Spectrogram showing how frequency content varies over time
- **D:** Simplified/processed spectrogram highlighting power of distribution across frequencies

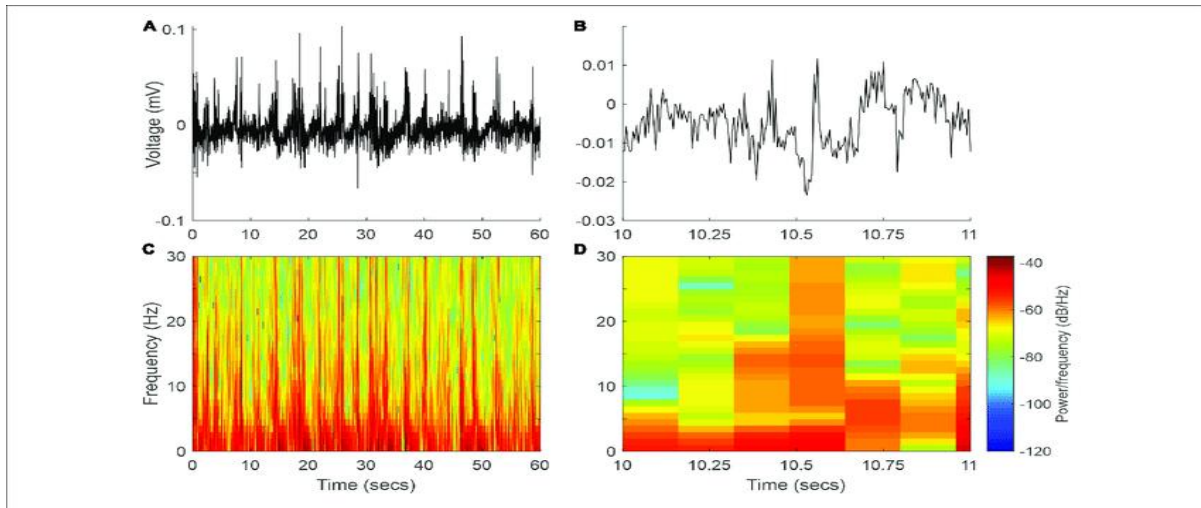
Overall, it illustrates the transformation from raw EEG signals to time–frequency representations used for analysis.

Second image is an **EEG spectrogram** that shows how brain signal frequencies change over time.

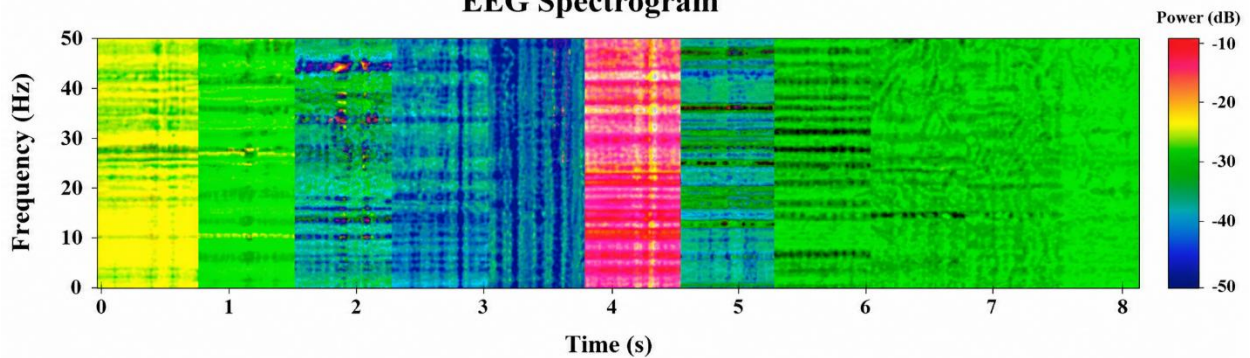
- The **x-axis** represents time (in seconds)
- The **y-axis** represents frequency (in Hz)
- The **color scale** indicates signal power (in dB), where warmer colors (yellow/red) show higher intensity and cooler colors (blue/green) show lower intensity

It visualizes variations in EEG activity, with noticeable changes in power patterns across different time segments.

EEG Image Processing



EEG Spectrogram



d. Convolutional Neural Network Classification

A basic CNN architecture used in this study includes the following components:

- **Input Layer** – Receiving EEG spectrogram images as input
- **Convolutional Layer** – Extracting important features using filters from the images
- **Activation Function (ReLU)** – Introducing non-linear transformation in the model
- **Pooling Layer** – Reducing data complexity and retains key features required
- **Flatten Layer** – Converting feature maps i.e. multi-dimensional arrays into a one-dimensional vector

- **Fully Connected Layer** – Learning intricate patterns configuration and maintaining relationships
- **Output Layer** – Producing the ultimate classification result e.g., image detected of the person is having dementia or is normal

The model automatically extracts spatial features from spectrogram images and learns discriminative patterns for classification.

e. Model assessment / Accuracy analysis

The model's efficacy is measured using metrics such as accuracy, precision, recall and F1 score. A confusion matrix is also used to scrutinize the cataloguing results. The validation techniques ensure dependability, despite the fact that assessments with prevailing or present approaches highlight the improvements in the result. The following step authenticates the model's capability to take a broad view and precisely classify the EEG patterns.

4. Implementation

The application of the CNN model is used for EEG signal classification. The following tools and libraries are used for implementation:

- Python
- NumPy
- Matplotlib
- TensorFlow / Keras
- Scikit-learn

5. Empirical Results

5.1 Model Evaluation Parameters and validation Metrics

To weigh the performance of the prototypical model, quite a lot of standard evaluation terms or metrics are activated. These metrics is used to measure the working of the model and provide a comprehensive and full thoughtfulness of the model's efficacy in the cataloguing of the tasks provided, particularly in the area of medical diagnosis states such as dementia detection using EEG signals and further more.

Accuracy: It is the most frequently used assessment metric or criteria which helps in representing the inclusive exactness or correctness of the model. It is defined to be as the proportional of fittingly prophesied instances in both positive and negative forecasts made of the total number.

It also provides a wide-ranging of ideas of how fine the model will executes; however, it may not be providing adequate result while dealing with imbalanced datasets, which are basically common in the area of medical applications generating result.

Precision: It will measure the amount of appropriately how many correct predicted were positive observations to the total predicted positive observations. It allows model to reflects on its ability to evade the incorrect positives predicted.

High precision also specifies that whenever the model predicts a positive class or response e.g., presence of dementia in the brain signal detection, it is highly probable to be exact or precise. This is predominantly more significant in clinical area sceneries to diminish the wrong diagnosis as output.

Recall: It also known as sensitivity i.e. it measures the part of genuine correct positive cases that are appropriately acknowledged by the model.

It accentuates on the model's ability to detect and identify all germane cases. In this context of detection of dementia, a high recall is critical to confirm about most of the patients coming with the disorder or condition are properly and accurately acknowledged, minimalizing the missed diagnoses and detecting the correct thing.

F1-Score: This is the harmonic mean of output related to precision and recall, providing a composed or balanced measure when individually both the false negatives as well as false positives are significant.

It is exclusively beneficial when there is an uneven or irregular class is being distributed. A higher level of F1-score specifies a balance which is improved between evaluation method of precision and recall, making it into dependable metric basically for assessing and classifying the performance majorly in healthcare applications.

Confusion Matrix: This matrix is primarily a tabular depiction of the model's performance and presenting the rapport between the actual and predicted classifications.

It is composed of four key elements:

- **True Positives (TP):** Occurrences where positive cases are correctly identified
- **True Negatives (TN):** Occurrences where negative cases are correctly identified
- **False Positives (FP):** Occurrences where negative cases are incorrectly classified as positive
- **False Negatives (FN):** Occurrences where positive cases are incorrectly classified as negative

The confusion matrix provides deeper insight into the types of errors made by the model and forms the basis for calculating other evaluation metrics such as accuracy, precision, recall, and F1-score.

5.2 Model Performance Assessment

In this the CNN-based spectrogram cataloguing model validates the following:

- Enabling automatic and further activating effective features for learning
- Achieving much better cataloguing precision than the traditional machine learning methods and techniques
- Minimizing the prerequisite for manual feature mining or extraction

Performance accuracy achieved is near by **85–95%** depending on dataset and preprocessing requirement and quality.

6. Real-World Applications

In the real-world the AI-based EEG spectrogram cataloguing can be pragmatic in the various ways. This tactic has wide range of applications in several domains of brain gesture scrutiny. It can be effectually better used for **neurological disorder diagnosis**, permitting the cases of early detection and treatment of conditions. It also acts a momentous role in system of **brain–computer interface (BCI)**, facilitating and making at ease the direct communiqué between the brain and external automatic devices. Furthermore, the technique supports and care about **emotional recognition** by scrutinizing EEG patterns recovered from system as well as **sleep stage classification** for nursing and refining sleep quality of the individual. Furthermore, it can be applied in **cognitive job load monitoring** scrutiny helping to evaluate mental exertion and also enhancement of human brain performance in multifaceted tasks and responsibilities.

7. Key Advantages of Spectrogram-Based Deep Learning Approach

This technique offers various benefits in EEG signal analysis. It effectually **captures and holds time–frequency information** allowing much better depiction of multifaceted brain signals. By upgradation and leveraging in deep learning study, it will **diminish the necessity for manual engineering feature** simplifying the inclusive procedure. This approach also **improves and expands the robustness** making it more dependable under changeable and varying conditions. Moreover, it is **scalable to multi-level class problems** aiding the cataloguing and arrangement of multiple brain statuses and conditions. Furthermore, this model is **appropriate for real-time enactment** and making it possible to implement the practical part for applications such as monitoring and assistive technologies and skills.

8. Disadvantages of CNN Using Spectrogram Representation

This approach also has certain limitations that needs to be considered. It mostly **requires large quantity of labeled datasets** for real and effective training of the model which can be problematic and time-consuming to obtain accuracy result. In addition to it the model also encompasses a very **high computational charge during training session** making it challenging and important processing for power and time. It is also **sensitive to things like noise and artifacts** which are present in EEG signals which can disturb accuracy of the output. Besides that there are **challenges in model interpretability** which makes it tough for understanding clearly how choices and decisions are made by the model.

9. Potential Future Developments

Future of the research work can emphasis on quite a few capable directions to make it much better and enhance EEG-based analysis systems. One vital zone is in the advancement of the **lightweight CNN architectures for edge devices** and also permitting processing on low-power hardware very efficiently. Integrating **explicable AI techniques for EEG interpretation** which can make progress in the area maintaining the transparency and belief in model verdicts. Also reconnoitering the **hybrid CNN–LSTM models** which may help in capturing both spatial and

chronological features of EEG signals much more excellently. The usage of **transfer learning approaches** can also diminish the prerequisite for large labeled datasets while **coalesced learning for confidentiality conserving EEG cataloguing** can also ensure security and decentralization of data which is being processed without negotiating about user privacy.

10. Conclusion

This research paper represents a inclusive AI-based outline for brain signal cataloguing using images of EEG spectrogram. This is done by altering EEG signals into time–frequency depictions and more enhancing them and leveraging them into CNN models. The system accomplishes high sorting the performance while minimalizing manual feature engineering. This methodology proves the strong probability in healthcare diagnostics, neurotechnology and brain–computer interface applications. With the progressions in lightweight architectures and explicable AI, the EEG-based deep learning systems are more projected to perform a critical part in the area of next-generation intellectual healthcare resolutions.

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