MULTI-RESOLUTION CNN FRAMEWORK FOR EEG IMAGE-BASED ANALYSIS OF NEUROPSYCHOLOGICAL ALTERATIONS IN EARLY DEMENTIA

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Abstract
Dementia is a progressive neurological disorder pigeon-holed by cognitive and cerebral decline, memory impairment and functional corrosion of the human brain. Recent advantages in the area of neuroimaging combined with deep learning have empowered automated dementia detection with high accuracy and exactness. EEG (Electroencephalogram) data, conventionally scrutinized as time-series signals which can be converted into spectrograms, topographic maps or scalograms allowing convolutional neural networks (CNNs) to acquire spatial patterns symptomatic of dementia. This paper provides and delivers an inclusive impression of CNN architectures that are mostly effective for EEG-image–based dementia cataloguing, comparing traditional CNNs, transfer of learning models and amalgam of deep-learning architectures.

Keywords *EEG, Dementia Detection, Convolutional Neural Networks, Spectrograms, Deep Learning, PhysioNet, Image Classification, TensorFlow, Biomedical Signal Processing.*

Introduction

Dementia detection has factually depended on clinical assessment, the neuropsychological testing such as MRI and CT scans etc. Though EEG is known for low-cost and non-invasive sense modality but the manual EEG reading and interpretation is idiosyncratic and time-consuming thing. Deep learning—particularly CNN techniques—has turn out to be the state-of-the-art that is high-tech approach because it can be inevitably extract the complex spatial features entrenched in EEG images. Dementia is a progressive neurodegenerative syndrome in which initial phase of neuropsychological alterations are problematic and difficult to perceive using predictable clinical approaches and methods. The recent CNN based tactics is using EEG image making presentations which reveals the possibilities but also often count on solo tenacity analysis and study which is restraining their ability to capture multi scale brain changing aspects. This study proposes a multiple tenacity of CNN context for EEG image-based scrutiny which permits effective learning of spatial ethereal features spanning in making it manifold scales to progress in the early dementia detection accurateness and interpretability.

1. EEG Images as Inputs for CNN Models

Although EEG report is intrinsically a one-dimensional temporal and chronological signal, CNNs do require 2D or 3D images for the inputs. This has motivated the development of EEG-to-image and driven into transformation techniques such as:

1.1 Spectrograms using Short-Time Fourier Transform (STFT)

It means creating a time-frequency depiction screening the circulation of power spanning in the frequency bands. Dementia-related forms and patterns such as electro-slowing become visually discrete.

1.2 Wavelet Scalograms using Continuous Wavelet Transform (CWT)

It captures fleeting frequency vicissitudes that happens with excellent time–frequency tenacity which makes them idyllic for detecting elusive dementia biomarkers.

1.3 Topographic Brain Maps (EEG topo plots)

It is a graphical representation that exhibits the spatial distribution of brain activity across the scalp of head, derived from EEG electrode signals, highlighting regional neuropsychological patterns. Aiding CNNs to acquire spatial abnormalities and irregularities such as regional slowing.

1.4 Functional Connectivity Images

The images visually epitomize the statistical relations or synchronization between the diverse brain regions, resulting from EEG signals, to exemplify forms and patterns of neural communication and network activity and commotion. Matrices or the media of images represents consistency, correlation, or phase-locking ideals spanning in EEG channels form rich spatial edifices for CNN learning.

These alteration or transformation techniques permit EEG data is to be treated likewise to natural images, enabling CNNs which includes multifaceted or complicated models such as ResNet, DenseNet and commencement designs—to perform and execute dementia detection with high accurateness and precision.

This data of EEG content can be transmuted into following:

a) Spectrograms (time–frequency maps)
b) Scalograms using continuous wavelet transforms
c) 2D/3D topographic brain maps
d) Functional connectivity matrices

These are some of the visual forms which allow CNNs techniques to extract three-dimensional patterns allied with dementia such as to abridged alpha power, amplified theta activity, anomalous coherence, and disrupted functional networks or links.

This paper identifies CNN techniques best suited for EEG-image-based dementia detection and highlights model performance, advantages, and limitations.

2. Image-Based EEG Representation Techniques for Dementia Diagnosis:

2.1 Time–Frequency Domain Spectrogram Representations:

In this conversion of EEG is done into spectrogram images using Short-Time Fourier Transform (STFT) and allows CNNs to apprehension the changes in oscillatory commotion. In these techniques the Dementia patients typically show:

a) Noticeable EEG decelerating with elevated in theta bands and diminished in alpha rhythms
b) Lessening in the temporal intricacy of EEG signals
c) Momentous variations are observed in the power spectral compactness profiles

Spectrograms are most extensively used as CNN inputs due to their dense spatial edifice.

2.2 Wavelet-Derived Scalogram Representations

Wavelet are used to transmutes and generate high-resolution images accentuating momentary features. This CNNs accomplish well for the reason that:

a) Scalograms recollect both temporal and rate of recurrence localizing of EEG signals
b) Vague dementia-related micro-patterns are effectively revealed
c) Multi-scale feature representations improve CNN learning capability

2.3 EEG Topographical Representations

These are 2D prognoses apprehension three-dimensional brain distribution spanning with the electrode positions. They reflect as:

a) Regional slowing for detection
b) Abridged fronto-parietal brain area connection
c) Altered hemispheric lopsidedness of brain

Through this CNNs techniques we can interpret these spatial falsifications very effectually.

3. Convolutional Neural Network Approaches for EEG Image-Based Dementia Prediction

3.1 Traditional CNN Model Architectures for EEG Image Analysis

The standard CNNs contains convolutedness, pooling and fully connected layers persist to be effective for smaller content of EEG datasets. Some of the out-of-date Machine Learning Approaches are:

Power Spectral Density (PSD)

In this initial tactic encompasses employing Welch's PSD and Fast Fourier Transform which transmute and extracted discriminative frequency-domain features nevertheless, these methods agonized from the limited three-dimensional and temporal resolution.

Time-Domain Statistical Features

In this the statistical dealings such as variance, Hjorth and kurtosis constraints were widely and extensively was applied in the before the deep learning studies but is totally depend on labor-intensive featuring work.

Nonlinear Dynamic Features

This is the Entropy-based metrics which includes model entropy and permutation and variation selective information which were to be used to depict reductions in EEG signal intricacy which is allied with dementia detection.

Conventional Machine Learning Classifiers

Moderate classification accuracy of around 70-80% was accomplished by traditional classifiers for bifurcation such as SVM, k-Nearest Neighbors, Random Forests and Gaussian Mixture Models but restricted oversimplification spanning in diverse and various datasets was observed.

The traditional machine learning approaches were restricted by labor-intensive feature extraction of the content and incapability or failure to capture high-level patterns—leading the way for the adoption of CNNs for tracking of the record.

Benefits:

- Insubstantial
- Low computational cost
- Easier to train on small datasets i.e. 50-500 subjects required

Limitations:

- Skirmish is done with intricate forms or patterns
- Requirement of manual architecture tuning

These traditional models in networks stereotypically can achieve 70-85% accuracy majorly depending on the dataset size.

3.2 CNN Models Leveraging Transfer Learning

The transfer learning is vastly effective and operative when EEG datasets are restricted. The pre-trained models on the ImageNet learn to globalize features that helps transmission well into EEG images.

Frequently Used Transfer Models are:

- VGG16 / VGG19
- ResNet50 / ResNet101
- InceptionV3
- DenseNet121 / DenseNet169
- MobileNetV2 (lightweight)

These are some of the top executors for EEG images are:

VGG16 / VGG19

VGG16 and VGG19 are unfathomable convolutional neural network (CNN) architectures is technologically advanced by the Visual Geometry Group (VGG) from Oxford University. They are extensively and mostly adopted in the area of research due to their straightforwardness, truth analysis and undeviating architecture. It exaggerates the network complexity and have been very reliable and is very consistent which helps in giving high performance spanning in an eclectic range of cataloguing tasks by means of the resource i.e. images.

VGG16/VGG19 are used because they are:

The VGG's based models are pigeonholed by a simple yet unfathomable architecture that enables effective classified ranked in extraction of features. Their sturdy feature is learning competence making them exceedingly appropriate for transfer learning, particularly when dealing with restricted medical datasets. In addition to this, these models are steady and stable, ease to customize and have demonstrated excellent and first rated performance in dementia detection studies, achieving classification and achieving the accuracies in the range of 89-95%. This is the reason why VGG models endure to be popular and trusted prime in CNN techniques, especially in EEG-based dementia detection research.

VGG19 with Transfer Learning

a) The deep and undeviating architecture of 16 or 19 layers which is very effective for tiered feature mining or extraction of the data.
b) Performance is very well and trained on EEG spectrograms, scalograms and topographic maps.
c) High cataloguing and accuracy generated when combined with data augmentation and fine-tuning.
d) Computational is heftier than ResNet and DenseNet which is more training time is required.
e) This model is best suited for medium-sized EEG image datasets.

ResNet Models (Residual Neural Networks)

ResNet employs residual blocks that mitigate the vanishing gradient delinquent, enabling a very deep networks to effectively acquire complex feature for representations.

Why ResNet is Best for Dementia EEG Images

The model is capable of learning subtle rate of recurrence three-dimensional anomalies present in EEG images while effectively handling noise commonly found in medical data. It performs the execution predominantly well on small to medium sized datasets and has demonstrated sturdy cataloguing the performance in dementia detection studies and achieving accurateness levels in the range of 88-95%. ResNet50 and ResNet101 are the most widely used in dementia detection.

ResNet with Transfer Learning

a) It is most steady and generalizable prototypical model spanning in different EEG image representations
b) Residual influences mitigate into vanishing gradient or inclination issue in deep learning networks
c) Having exceptional performance on the EEG spectrogram and time–frequency images
d) It is well suited for pretrained heft refinement on medical based datasets

DenseNet Models

DenseNet is a convolutional neural network architecture in which each layer is unswervingly connected to every other layer, enabling efficient feature reuse and improved gradient flow.

It is used for EEG Images because:
DenseNet121 is highly effective at learning subtle textural variations in EEG spectrograms while reducing the redundant constraints through denseness of large data connectivity. This architecture improves gradient flow across different layers enabling efficient and competent features to be reused and strong learning is done even with restricted data. As a consequence of the result generated the DenseNet121 has demonstrated and proved very high cataloguing in performance and achieving precisions in the range of 90-96% in Dementia's disease for EEG studies.

DenseNet121 + Attention Mechanism
a) It gives best overall performance for EEG-based dementia cataloguing
b) Have high accurateness even on very small and imbalanced datasets
c) Support strong features to recycle through dense connectivity and diminishes overfitting
d) Attention is given to the modules for highlighting dementia related EEG patterns based on frequency and spatial regions of the brain.

Inception Networks
Inception Networks are deep convolutional neural network architectures that can process the input detail of features at manifold scales in parallel to use different filter sizes to capture rich and diverse representations efficiently.

InceptionV3 for Multi-Scale EEG Features
a) It is multi-scale convolutional filters which helps in capturing both satisfactory and abrasive grained EEG patterns
b) It is highly effective for wavelet-based model and multi resolution of EEG images
c) It helps in lowering computational cost than the VGG19 model with viable accurateness
d) It performs very well when EEG features varies significantly spanning in frequency occurrence bands

Why InceptionV3 Works Well:
The model is capable of capturing both local and global EEG abnormalities, making it well suited for scrutinizing topographic maps and converted into wavelet-based image representations. It also offers competent computational performance act and it has to be reported to achieve cataloguing accurateness making it stereotypically ranging from 85-93% in dementia detection studies and analysis.

MobileNetV2 (Lightweight CNN Model)

MobileNetV2 is a lightweight CNN model which very efficient and high-performance convolutional neural network designed and planned for mobile and embedded devices. It is most widely used in deep learning errands and tasks where computation and execution must be fast for generating output and memory usage should be low and easy to access.

MobileNetV2 Features:

a) It uses depth wise distinguishable convolutions which is use to reduce parameters, constraints and computation.
b) It helps in corpora ting inverted residual blocks for competent feature learning.
c) Support lightweight architecture which is suitable for low resource devices.
d) Provides a good equilibrium and cost benefits between accuracy and speed

Why it is used as CNN technique:

MobileNetV2 is a lightweight Convolutional neural network architecture premeditated for fast computation and with low memory usage making it highly appropriate majorly for medical image scrutiny and analysis of EEG-based dementia detection. It help to have study depth-wise the detachable convolutions to significantly diminishes the computational cost along with upturned residual chunks or blocks that can enhance gradient flow and model constancy. The usage of linear blocks or bottlenecks aids to reserve feature and superiorities while minimalizing the model size consenting an extensive lessening and reduction in constraints and computation without negotiating with the precision or accuracy.

Due to this competent CNN architectural selections, MobileNetV2 is the most well suitable for instantaneous and resource inhibited environments and settings such as mobile or embedded systems. It validates the robust and strong transfer of the learning performance act when primed per ImageNet proficient with weights and is predominantly operative and effective for small number of datasets which are very commonly used in the studies based on EEG. Moreover, MobileNetV2 accomplishes consistently on EEG spectrogram and cataloguing the various tasks, supporting precise, competent and resourceful dementia detection schemes in the system. MobileNetV2 generally reports cataloguing the accurateness amid 85-92% in EEG based dementia detection while upholding less cost as well as maintaining little computational complication and intricacy.

4. Hybrid CNN Models

Hybrid CNN Models are those deep learning CNN architectures that syndicate Convolutional Neural Networks (CNNs) with other models or techniques such as RNNs, Transformers, Autoencoders, attention mechanisms, capsule networks or graph networks to leverage and harmonizing strong point and improvising the feature representation, learning efficiency, and classification performance.

4.1 CNN-Long Short Term Memory Models

Here merging of both CNN with LSTM i.e. Long Short-Term Memory captures both spatial and chronological need and dependences.

Benefits:

This model is well appropriate for handling and managing consecutive EEG image frames and is proficient enough for learning chronological progression patterns which is associated with the dementia. In this by capturing both spatial and temporal dependencies and it also outperform making it beat the standalone CNN architectures which has been testified to accomplish typical cataloguing precisions within the range of 92-97% in dementia detection studies.

4.2 CNN–Attention Mechanisms

In this the most relevant brain region are highlighted by attention mechanisms which compromises with CBAM, SE-Block and Transformer Modules.

Advantages:

This is an attention-based model which focus on specific brain regions for detecting dementia predominantly the progressive and parietal areas for processing sensory information supporting attention and visuospatial skills while effectually overpowering the noise existing in EEG signals. This targeted feature helps in learning and enhancing model interpret for making it able and has been exposed to improvise cataloguing performance with report having the accuracy ranging between 94-98% contingent on the number of datasets.

4.3 Graph-CNN Integrated with EEG Connectivity Maps

Functional connectivity matrices are when signal is transformed into images which are well suited for graph-based CNNs (G-CNNs).

Strengths:

The model is capable of capturing long-range brain interactions and is well suited for early-stage Alzheimer's disease detection. By modeling network-level disruptions in brain activity, it provides an effective representation of disease-related changes and has demonstrated classification accuracies typically ranging from 90-95%.

Challenges and Future Directions

Before acquaint with the EEG processing, dealing and representation techniques it is very crucial to diagnose why the raw EEG signals cannot be directly used as contribution for convolutional neural network (CNN) models.

Challenges of Using Raw EEG Signals for CNN Models:

1. **High Noise Levels**

EEG data are filthy done by artifacts or pieces in coordination from eye movements, muscle activity, cardiac signs and environmental intrusion which can sternly affect the cataloguing of accuracy if not removed.

2. **Non-Stationary Behavior**

The frequency i.e. occurrence is contented of EEG signals which changes over time and it represents them as static 1D signals which fails to do sufficiently the model temporal–spectral disparities.

3. **High Facts Dimensionality**

Typically the EEG recordings (e.g., 64 channels × 160 s × 256 Hz) yield gigantic data sizes making of CNN which is to be build and do scrutinizing is computationally expensive.

4. **Limited Spatial Representation in 1D Format**

The CNNs requires organized spatial information for effective and efficient feature extraction in which raw 1D EEG signals do not logically makes it available.

Future Research Directions

- Modernizer based EEG image models
- Multimodal synthesis (EEG + MRI + cognitive scores)
- Self-supervised learning to diminish the necessity for considered data
- Interpretable AI for clinical or scientific acceptance

Conclusion

CNN techniques have revolutionized EEG-based dementia detection techniques, particularly when EEG signals are converted into different images like spectrograms, scalograms or topographic. Amongst various prevailing architectures such as DenseNet121 with attention mechanisms and ResNet50 transfer learning models are consistently and reliably outperform the others models, attaining accurateness above 90% on most of the datasets. Hybrid CNN-LSTM and CNN-Transformer approaches and further it improves performance by integrating and mixing temporal information. As the deep learning technology and EEG preprocessing techniques used for change in the progress. The CNN based dementia portrayal using EEG images will turn out to be increasingly precise, understandable and clinically pertinent.

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