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Electroencephalographic Biomarker Detection For Dementia Using Convolutional Neural Network-Based Analysis: A Causal And Outcome-Oriented Study

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Abstract
Dementia encompasses a spectrum of progressive neurodegenerative conditions that gradually erode memory, cognitive abilities, and behavioral functioning, severely diminishing quality of life. Traditional diagnostic practices often rely on clinical assessments and neuroimaging, which may be costly or lack early-stage sensitivity. In contrast, electroencephalography (EEG) has emerged as a non-invasive, cost-effective tool capable of capturing subtle neural abnormalities linked to cognitive decline.

With the rise of artificial intelligence (AI), particularly deep learning, novel approaches have surfaced for analyzing complex biomedical data. Among them, Convolutional Neural Networks (CNNs)—renowned for their strength in image and signal processing—offer significant promise in interpreting EEG signals for dementia detection. By learning spatial and temporal patterns directly from EEG recordings, CNNs can identify characteristic changes in brain activity associated with various stages of dementia.

This paper delves into the dual facets of this approach: the ***cause****, examining why EEG signals are suitable for dementia diagnosis and how CNNs process them; and the* ***effect****, exploring the practical outcomes, clinical relevance, and challenges of adopting this methodology. We first investigate the neurophysiological alterations induced by dementia and their manifestations in EEG patterns. Early and precise identification of these signatures is crucial for timely intervention and improved long-term care.*

Through comprehensive literature analysis and empirical findings, we highlight how CNN-based models consistently outperform traditional machine learning techniques and even expert evaluations in some scenarios. The adoption of such systems in clinical and research environments has shown promising outcomes—ranging from increased diagnostic accuracy and early detection capabilities to economic scalability and improved patient management.

Nonetheless, this paradigm is not without limitations. Issues such as inter-subject variability in EEG data, black-box behavior of deep learning models, and ethical implications surrounding data privacy and algorithmic fairness must be addressed. To that end, we propose forward-looking strategies, including multi-modal diagnostic frameworks, federated learning for privacy-preserving model training, and the development of explainable AI (XAI) to foster transparency and trust.

Ultimately, integrating EEG with CNN-based analysis holds transformative potential in redefining how dementia is detected and managed—offering a pathway toward accessible, scalable, and non-invasive neurological diagnostics.
Keywords: *Dementia, EEG, CNN, Neurological Diagnostic, Cognitive monitoring*

1. INTRODUCTION

Dementia is not a sole disease but a syndrome resulting from various neurological conditions, the most disorder in cognitive function being which is divided in to Major Neurocognitive Disorder (MND), vascular dementia, Lewy body dementia, and frontotemporal dementia. These conditions of mental health share a mutual feature: progressive, advance, irreparable and irreversible decline in cognitive functions of the brain. In today's world globally, an estimated 55 million people worldwide are living with dementia. This number is projected to increase significantly, with estimates reaching 78 million by 2030 and 139 million by 2050, according to the World Health Organization (WHO).

Dementia incorporates a range of cognitive disorders of mental state categorized by the weakening and decline of brain functions, which includes memory loss, confusion, and diminished reasoning and logics. The loss in the memory, this disease is the very common form, just like keeping the record for 60-80% of dementia cases. The early finding and diagnosis is vital for executing treatments that can slow progression in mental state and improve patient outcomes with help in recovery.

The old style traditional diagnostic tools, which include neuroimaging (MRI, CTscan), neuropsychological evaluation, assessments, and blood tests. Nevertheless, these are often very expensive, aggressive, laborious and time-consuming process. EEG method, by effect of discrepancy, is a profitable, rewarding, lucrative, non-invasive technique of monitoring indications done by electrical brain bustle. Changes that happen in the EEG patterns of the patient can give signal and indicate the start or onset and progression of dementia in human brain.

With the advent of deep learning, predominantly the CNNs techniques, automatic analysis of reflex of EEG signals has developed a strong and potent tool for early stage of dementia detection. CNNs are able to extract hierarchical or tiered features from raw EEG signals or with their converted representations in image form (e.g., spectrograms), which provides a powerful method for classification of disease in different levels. Electroencephalography (EEG), is a technique that can deal and measure electrical activity of the brain done over by electrodes positioned on the human scalp, which is increasingly being efficient and explored as a cost-effective and non-invasive technique another alternative for dementia diagnosis. EEG affords an instantaneous view of brain dynamics or real time actions and is sensitive to functional changes happening in neuronal networks, which are every so often detected and altered in dementia occurrence.

Currently developments in artificial intelligence, particularly in the area of deep learning, have revolutionized and developed medical signal scrutiny. Among all the other deep learning techniques, Convolutional Neural Networks (CNNs) have gained enough prominence due to their ability to acquire and learn hierarchical features from raw or triflingly processed input which is negligible. Originally this method was developed for image recognition, CNNs technique can also process the EEG signals in 2D formats (e.g., spectrograms or wavelet transforms) to perceive subtle, refined and multifaceted or complicated patterns with cognitive connected for making deterioration happening in the functioning of the human brain.

In this paper, we examine the cause the neurobiological basis of EEG abnormalities in dementia and the computational rationale for using CNNs techniques and the effect in the real-world applications, performance metrics for measurement, and insinuations of CNN-based technique with EEG image analysis in dementia diagnosis of the human brain.

2. EEG in Dementia Diagnosis

2.1 Understanding EEG Signals

EEG captures the brain's electrical activity by recording voltage changes caused by ionic currents flowing through neurons. These electrical signals are categorized into distinct frequency bands, each reflecting specific brain states and cognitive functions.:

- **Delta (0.5–4 Hz)** – Deep sleep; slow waves.
- **Theta (4–8 Hz)** – Drowsiness or early stages of sleep.
- **Alpha (8–12 Hz)** – Relaxed wakefulness.
- **Beta (12–30 Hz)** – Active thinking and concentration.
- **Gamma (30–100 Hz)** – Binding of Information from different brain area.

In hale and hearty individuals, EEG signals are organized, symmetric, and contain a characteristic of balanced distribution of these frequencies in brain signals. In dementia, exclusively for the forgetfulness disease, EEG signals become slower, less synchronal, and more capricious.

2.2 EEG Abnormalities in Dementia

Studies have unswervingly shown how the EEG can depict deviation in the signal:

- A diminution in alpha and beta influence.
- Reduction in signal complexity and functional connectivity.
- Reformed entropy, lucidity, and phase synchroneity.

- An increase in theta and delta wave activity reflects underlying neural deterioration and is often associated with cognitive decline in dementia

EEG reflects cortical dysfunction and degeneration in neural circuits, making it a valuable tool for monitoring dementia. As the disease progresses, EEG changes indicate declining brain function. Thus, EEG can act as a non-invasive, functional biomarker to track the progression and severity of dementia-related neurological deterioration over time.

2.3 Advantages of EEG study for

- Non-invasive and safe - non-surgical and secure
- Low-cost and portable - Cheap and easily deployable
- Fine-grained temporal precision – Enables swift tracking of brain activity changes
- Adaptable for real-time applications – Ideal for continuous and immediate brain monitoring

2.4 Limitations of Manual EEG Interpretation

Human connoisseurs' skirmish to manually understand and classify dementia-related EEG image patterns due to:

- High inter-subject variability *- Significant differences in EEG patterns among individuals*
- Subtle signal abnormalities - Minor or hard-to-detect changes in EEG signals
- Noisy or artifact-laden recordings - EEG data often contains interference from external or internal sources

These features make EEG idyllic for repeated monitoring and comprehensive screenings, exclusively in under-resourced settings.

2.5 EEG as a Biomarker for Dementia

Electroencephalography (EEG) captures the brain's electrical activity, reflecting neural oscillations that are essential for cognitive functions. In dementia-related disorders, specific alterations in EEG patterns have been consistently observed. These include a reduction in alpha power (8–12 Hz), which is associated with cognitive slowing, and an increase in slower wave activity such as theta (4–7 Hz) and delta (0.5–4 Hz) bands, indicating cortical dysfunction. Additionally, there is a noticeable decline in the complexity and synchronization of brain signals, pointing to disrupted neural connectivity. While these changes may not always be easily visible through standard visual inspection of EEG traces, they can be effectively detected using advanced signal processing methods and machine learning algorithms. Automated analysis is crucial to ensure reproducibility, handle large-scale data efficiently, and enable real-time clinical applications. Therefore, integrating computational techniques into EEG analysis offers a promising pathway for the early and accurate detection of dementia and related neurological disorders.

3. CNNs and EEG Signal Processing

3.1 Introduction to CNNs

Convolutional Neural Networks are the class of deep learning models predominantly operative for scrutinizing data with grid-like analysis situs of the image of brain (e.g., images like spectrograms). A CNN inevitably **learns features** from input data and uses them to **catalogue** or **scrutinize** patterns form. It's extensively used in tasks like image recognition, and speech processing and medical diagnosis. Key components of CNNs include:

- **Convolutional layers**: Apply filters to extract features. Feature maps that highlight important characteristics of the input.
- **Activation functions**: Introduce non-linearity (e.g., ReLU - Rectified Linear Unit). This the technique of converting negative values to zero and this makes the positive values unbothered.
- **Pooling layers**: Down sample features to reduce dimensionality. Lowers computation, reduces overfitting, and captures dominant features.
- **Fully connected layers**: Interpret features for classification. Combines features to make final predictions (e.g., classification into dementia/non-dementia).
- **Output layer**: Probabilistic class assignments. Improves generalization on unseen data. Softmax algorithm activation for binary (Dementia/Non-Dementia) or multi- class output.

3.2 Adapting CNNs to EEG

EEG signals are inherently temporal, capturing the brain's electrical activity over time. However, to leverage the powerful pattern recognition capabilities of Convolutional Neural Networks (CNNs), these 1D time-series signals are often transformed into 2D image-like representations. This conversion enables CNNs, which are traditionally designed for image data, to effectively analyze and interpret EEG signals.

One common approach is the use of **time-frequency spectrograms**, generated through Short-Time Fourier Transform (STFT). These spectrograms display how the frequency content of the signal evolves over time, providing a detailed view of brain activity patterns. Another method involves creating **scalograms** using wavelet transforms, which capture localized frequency changes with high resolution. This is especially useful for identifying transient events or subtle signal abnormalities associated with neurological disorders.

Additionally, **topographical maps** based on the spatial arrangement of EEG electrodes are used to visualize the distribution of brain activity across different regions of the scalp. These maps offer spatial context that is crucial for detecting region-specific abnormalities seen in dementia. By converting EEG signals into these 2D representations, CNNs can learn complex spatiotemporal features that are indicative of cognitive decline, enabling more accurate and automated dementia detection. CNNs are well-suited for handling structured, grid-based inputs such as images or time-frequency representations, which makes them highly effective for analyzing EEG data. Their main strengths include:

- **Learning features automatically:** CNNs can identify relevant patterns from raw input data on their own, eliminating the need for handcrafted feature extraction.
- **Robustness to spatial shifts:** They can recognize patterns no matter where they appear in the input, making them flexible in detecting features that may vary in position.
- **Layered pattern recognition:** The network builds knowledge in stages—initial layers capture simple elements like edges or frequency shifts, while deeper layers combine these to recognize more sophisticated, abstract features.

3.3 Training and Optimization of CNN in research with EEG report:

- **Data Augmentation**: Helps reduce model overfitting when training on limited data samples.
- **Transfer Learning**: CNNs initially trained on broad EEG-related tasks can be adapted or fine-tuned specifically for dementia classification.
- **Cross-validation**: Ensures sturdiness and generalization in the samples.
- **Loss Functions**: Usually categorical cross-entropy. Encourages the model to output probabilities that are as close as possible to the accurate marker.
- **Optimization Algorithms**: Adam, SGD with momentum, RMSprop.

4. METHODOLOGY OVERVIEW

4.1 Data Collection and Preprocessing

Typical datasets include from different public and private resources like Kaggle, Github, Private hospital/clinical datasets. The preprocessing steps includes the following:

- **Artifact removal** (e.g., eye blinks, muscle activity) using ICA or filtering.
- **Segmentation** into fixed-length epochs (1-5 seconds).
- **Feature extraction**: Raw signal, spectrograms, coherence maps, etc.
- **Normalization** to maintain consistency across recordings.

4.2 Evaluation Metrics: Model performance is evaluated using:

- Accuracy
- Precision, Recall, F1-score
- ROC-AUC (Area Under Receiver Operating Characteristic)
- Confusion Matrix

Cross-validation and patient-wise data partitioning help prevent overfitting and promote robust model generalization across unseen subjects. Commonly used models by CNN techniques for dementia detection are: EEGNet, DeepConvNet, VGG-like CNNs adapted for EEG. Here are studies of different case and review of their Performance.

➢ **Case Study 1: Dementia Detection Using Spectrogram CNN**

- Dataset: 250 subjects (84 Dementia Patient, 56 controls).
- STFT Method: Short-Time Fourier Transform pragmatic in EEG image to CNN learning.
- Accuracy: 94%, AUC (Area under the curve): 0.94.
- Comprehension: Alpha-band features from the frontal and parietal regions were the primary focus of the CNN.

➢ **Case Study 2: DeepConvNet on Raw EEG**

- Dataset: Public Github dataset.
- Architecture: 5-layer CNN with dropout.
- Performance: 89% accuracy; F1-score: 0.87.
- Conclusion: Mild cognitive impairment (MCI) could be distinguished from normal aging using a CNN

➢ **Case Study 3: EEGNet-Based Transfer Learning Approach from EEG of Elderly cohort**

- Dataset: Private hospital data.
- Result: Improved performance from 81% to 92% after fine-tuning.
- Application: Real-time bedside monitoring tool.

4.3 Comparative Analysis

The comparative analysis of three deep learning models—EEGNet, DeepConvNet, and STFT-CNN—highlights their varying performance in EEG-based dementia detection. EEGNet, utilizing raw EEG signals, achieved an accuracy of 86% with an AUC of 0.85, and required minimal training time, making it suitable for lightweight applications. DeepConvNet, which processes EEG as time-series data, demonstrated improved accuracy at 89% and an AUC of 0.87, albeit with moderate training time. Notably, STFT-CNN, which leverages spectrogram representations through Short-Time Fourier Transform, outperformed the other models with an accuracy of 94% and an AUC of 0.94, though at the cost of higher computational demand and longer training duration. These results suggest that while all models are effective, STFT-CNN offers superior classification performance when computational resources allow. CNNs outperform SVMs, Decision Trees, and Random Forests, especially on complex, high-dimensional EEG data.

5. Cause and Effect Analysis

5.1 Causes: Why This Approach Works

- Complex and High-Dimensional EEG Data
- Need for Early Detection
- Automation and Scalability
- Cost-Effective, Non-Invasive Screening
- Real-Time and Continuous Monitoring
- Superior Accuracy Over Traditional Methods

5.2 Effects: Outcomes of CNN-based EEG Dementia Detection

- **Boosted Diagnostic Precision:** Recent convolutional neural network (CNN) models have achieved remarkable accuracy—ranging from approximately 95% up to a record-high 99.28% on specific medical imaging datasets—rivaling or surpassing expert-level diagnostic performance
- **Non-Invasive Primary Screening:** With the growing availability of affordable, portable EEG devices and the enhanced accuracy of CNN-based diagnostic tools, these systems are increasingly suited for large-scale neurological screening in community health programs—especially in low-resource and remote settings. This reflects the current scenario where EEG hardware is becoming more cost-effective and CNN models are more deployable due to improved edge-computing compatibility and open-source frameworks.
- **Real-Time Specialist care and Prognosis:** CNNs can be efficiently deployed on edge devices such as wearable EEG headbands or portable monitoring units, enabling real-time, continuous assessment of brain activity in elderly individuals—facilitating early detection of cognitive decline even before noticeable clinical symptoms emerge, especially in home-based and remote care settings.

- **Interpretability and Biomarker Detection:** Techniques like such as Layer-wise Relevance Propagation (LRP) and SHapley Additive exPlanations (SHAP), Grad-CAM and saliency maps allow clinicians to visualize which EEG features contribute most to the model's decisions, potentially revealing new electrophysiological biomarkers.

5.3 Ethical and Practical Considerations

In the application of CNN techniques for dementia detection using EEG data, several ethical and practical challenges must be addressed to ensure responsible deployment. **Data privacy** is a primary concern, as EEG recordings and associated medical information are highly sensitive. It is essential to implement robust data protection protocols to prevent unauthorized access and ensure compliance with healthcare privacy regulations such as HIPAA or GDPR. Additionally, **bias and fairness** must be carefully evaluated. Deep learning models should generalize well across diverse patient populations, including variations in age, gender, and ethnicity, to avoid diagnostic disparities. Failure to ensure fairness may lead to unequal treatment outcomes and undermine trust in AI-assisted diagnostics. Finally, **clinical integration** of such models is not straightforward; it demands thorough validation, regulatory approval, and the support of physicians. Gaining clinician buy-in is critical, as they need to understand, trust, and effectively use the model's output in their decision-making processes. Without addressing these factors, even the most accurate AI system may face resistance or ethical challenges in real-world healthcare environments.

6. CHALLENGES AND LIMITATIONS

- **Data Imbalance**: Clinical datasets often skewed toward certain age groups are resembling the dataset in particular format.
- **Generalizability**: Models trained on one dataset may not work elsewhere so it is not general system but only do like job displacement.
- **Interpretability**: CNNs learn complex pattern (e.g. EEG signal) but does not clear understanding about what is the logic behind the decision making.
- **Computational Costs**: Training deep models can be resource-intensive that is learning output from large Datasets. (e.g. For Dementia Detection from EEG signal)
- **Data Scarcity and Privacy:** Medical EEG datasets are limited and sensitive. Privacy laws (like HIPAA/GDPR) hinder data sharing. Artificially generating of data and amalgamated learning are potential and probable solutions.
- **Inter-Subject Variability:** EEG signals vary significantly across individuals. Personalized models or transfer learning approaches may improve performance.
- **Artifact Management:** It refers to signal noise**.** CNNs can misinterpret artifacts (e.g., muscle noise) as disease signals. Preprocessing must be robust, or artifact-aware training strategies should be adopted.

7. FUTURE DIRECTIONS

Future research in EEG-based dementia detection using Convolutional Neural Networks (CNNs) should focus on several key areas to enhance clinical utility, generalizability, and scientific insight.

- **Explainable AI (XAI):** Visualizations techniques can show which EEG sections contributed to the forecast, increasing and growing the clinician trust.
- **Multimodal Fusion:** Merging all the results like EEG with MRI, PET, and clinical scores can improve and get more accurate and resilience to noise.
- **Personalized Models:** Transference of learning and domain adapting to a technique can help seamster models to discrete and individual patients.
- **Amalgamated Learning:** Facilitates model training across decentralized data sources while preserving data privacy and minimizing the need for data sharing
- **Integration with IoT and Wearables:** Low-power EEG sensors is embedded in headbands could collect data continuously non-stop, enabling passive or reflexive dementia monitoring through the signal of the brain.
- **Lightweight Models for Mobile Devices:** Edge AI keys can democratize i.e. accessible or used by everyone, permit access to dementia detection tools in countryside and isolated areas.
- **Longitudinal Studies:** Tracking down the EEG patterns over a period of time can give assistance to predict or foresee disease progression and can also evaluate the treatment for healing effectively.

8. CONCLUSION

The application of Convolutional Neural Networks (CNNs) to electroencephalographic (EEG) analysis represents a significant advancement in the early and accurate detection of dementia. This deep learning-based approach addresses several limitations inherent in traditional diagnostic methods by offering a scalable, non-invasive, and efficient alternative that is well-suited to diverse healthcare settings. EEG's ability to non-invasively record real-time brain activity makes it an accessible tool, and when paired with CNNs, it enables the automatic extraction of complex features indicative of early-stage or even preclinical dementia.

The rationale for adopting this approach is rooted in the well-documented physiological alterations in EEG patterns associated with neurodegenerative decline, which CNNs can detect through their capacity for hierarchical and data-driven feature learning. As a result, this methodology offers numerous benefits, including enhanced diagnostic precision, cost-effective population-level screening, and the potential for real-time, continuous cognitive monitoring.

Although the results are encouraging, several significant hurdles remain. Key concerns such as data privacy, model bias, and integration into clinical practice require thoughtful and rigorous attention. Moreover, the successful integration of such technologies into real-world clinical workflows requires rigorous validation, transparency, and collaboration with healthcare professionals. Future directions such as explainable AI, federated learning for decentralized data training, and multimodal data fusion are likely to accelerate the adoption of CNN-based EEG diagnostics. As these advancements continue, this approach holds the potential to transform the global landscape of dementia diagnosis and management.

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