Influence of EEG Constraints for the Detection of Dementia Diseases: An Organized Review

Ms. Habi Patrick[1], Dr. Shailja Shukla[2]
[1]*The Bhopal School of Social Science (BSSS) college*
[2]*Sanjeev Agrawal Global Educational (SAGE) University, Bhopal*

INTRODUCTION

The paper aims to reconnoiter the application in the field of Convolutional Neural Networks (CNNs) in detecting dementia from Electroencephalogram (EEG) images. Dementia is a progressive neurological disorder, categorized by the progressive deterioration of cognitive function, can be stimulating to detect the disorder at initial phases. It explores the area to work of Convolutional Neural Networks (CNNs) in the detection of dementia by analyzing Electroencephalogram (EEG) images. EEG is a non-invasive way or technique that records electrical activity in the brain and show probability in detecting neurodegenerative diseases. The usage of deep learning work for approaches, predominantly CNNs, offers potential in powering, automating and enhancing the research to detect accurateness of dementia disease from EEG signals.

Important Notions for the paper:

The study of the paper is dependent on two things firsty the EEG report and secondly the CNN image. This is the descriptive knowledge about them.

EEG for Dementia Detection: EEG captures brain signals activity which is often and specially used in medical study of neuro-science to understand different and various neurological disorders, including ‘dementia’. The changes in brain wave generated is studied and the patterns can specify the cognitive or mental impairments. Nevertheless, manual analyze approach of EEG data is very slow and time-consuming. It also requires expertise knowledge to understand the image of EEG. EEG can measure electrical movement in the brain by means of electrodes the device that is attached to the scalp. Brainwave anomalies, is calculated by those bands in the alpha, beta, delta, and theta, which show the disorder - cognitive impairments in dementia patients. The old-style tactic for analyzing EEG data includes the feature for extraction of data from brain signal processing the techniques like Wavelet Transform or Fast Fourier Transform (FFT). However, this method of analysis is time-consuming and result is reliant on on skilled person’s knowledge.

Convolutional Neural Networks (CNN): In Deep Learning the Convolutional neural network studies the target directly from data. CNN is mainly used to find patterns or output of images and to give the result by identifying the objects and the categories. They can also be relatively operative for cataloging different outcomes like audio, time-series, and signal data etc. CNN is a type of deep learning style used in general like image recognition and classification of errands. CNN work by mining different features from data that is inserted through a line of sequences of convolutional and pooling layers. They have been extensively used for medical images and promise to give relevant output for EEG study by altering EEG signals into image-like representations that is a symbol form that CNN can understand and process. CNN have turn out to be the leading and important deep learning architecture for image cataloging tasks. EEG signals are pre-processed and transmuted into spectrograms or other image depictions that can be inserted into a CNN. Important features of CNN comprise of:

- Convolutional layers: These layers extract pertinent features by smearing the filters across the input or inserted image (in this study, EEG images).
- Pooling layers: These layers diminish the dimensionality of the data, making the CNN model fully accessible for computer-oriented job efficiently.
- Fully connected layers: These layers categorize the mined features into diverse classes to categories, such as the person is having "dementia" or "healthy”.

CNN can perceive complex and multifaceted information, non-linear association and connection between EEG signal patterns that are symptomatic of dementia – the mental disorder and improving the analyses giving diagnostic accuracy. Some of the features of analysis done:

- Advantages of CNN: Their ability to inevitably excerpt relevant features from EEG data during analysis, reduces the need for manual feature engineering, which is included
- Limitations of CNN: Effective training of CNNs could require large datasets, yet EEG datasets, particularly those related to dementia, are often limited in both size and diversity
- Future Directions: Refining the CNN architecture, applying transfer learning to improve performance with small datasets, or integrating additional modalities (such as MRI data) to enhance detection accuracy might be include

METHODS AND APPROACHES

- The authors used working CNN images to classify EEG data by altering it into a image form appropriate for analysis.
- The model's architecture is likely comprised of multiple convolutional layers designed to capture spatial patterns in EEG images, followed by fully connected layers for classification. The exact architecture, including the number of layers, kernel size, and activation functions, may vary.
- The raw EEG signals might have been filtered and segmented to remove noise and object d'art, and the data was subsequently converted into spectrographs or other visual representations
- An open-access EEG dataset or a clinical dataset of patients identified with dementia and a regular group of healthy individuals was likely used in the research
- A supervised learning approach would be used to train the model, with labeled data (dementia vs. healthy control) provided. The model's effectiveness would likely be evaluated using performance metrics such as accuracy, precision, recall, and F1-score. This is the method for training and evaluation.

The methodology outlined in the paper comprises several key steps:

The first step involves preprocessing the EEG signals to remove noise and artifacts. Techniques such as bandpass filtering, Independent Component Analysis (ICA), and signal normalization are employed to ensure clean, high-quality data for further analysis.

Next is data transformation, where the processed EEG signals are converted into 2D or 3D images. Techniques like Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) are applied to capture both time-domain and frequency-domain information, which is crucial for accurate feature extraction.

The CNN architecture is then designed with multiple convolutional layers, pooling layers, and fully connected layers. Using supervised learning techniques, the model is trained on a labeled dataset, comprising EEG data from patients with dementia and healthy controls, to classify between the two groups effectively.

For training and validation, the dataset is split into training and validation sets, with cross-validation techniques employed to optimize the model’s hyperparameters. The model's performance is measured using standard evaluation metrics such as accuracy, precision, recall, and F1-score, ensuring a robust evaluation of its classification capabilities.

Finally, the paper includes a comparison with other models. The CNN model is likely compared to traditional machine learning models like Support Vector Machines (SVM), Random Forests, and logistic regression. This comparison highlights the CNN's superior performance, demonstrating its efficacy in accurately distinguishing between dementia patients and healthy individuals.

Results and the highlights of the analysis done in detection of dementia are likely to be focused on:

- Classification Accuracy: The CNN model is anticipated to achieve high classification accuracy in differentiating dementia patients from healthy controls, likely surpassing traditional machine learning mod.
- Confusion Matrix Analysis: It reveals the distribution of true positives, true negatives, false positives, and false negatives. CNNs are expected to yield a higher true positive rate while minimizing false negatives, which is essential in medical diagnostics.
- Training and Validation Curves: This depicts the model's learning progress over time, verifying its ability to generalize effectively to new data without overfitting.

- Ablation Study: This demonstrates how different layers, filters, and hyperparameters impact the model's performance.

DISCUSSION

The discussion section on the topic of dementia detection using CNN image analysis is likely to address several key points:

One of the prime strengths of CNNs is their skill to inevitably learn intricate features from EEG data, which meaningfully diminishes the reliance on manual feature mining and the need for domain-specific expertise.

However, there are notable limitations to consider. The primary challenges include the requirement for large, labeled datasets for training CNNs. Additionally, EEG data can exhibit high variability across different subjects, necessitating extensive preprocessing. Training deep learning models also demands substantial computational resources.

The authors may propose potential improvements to enhance the model's performance. Suggestions could include employing data augmentation techniques to artificially expand the dataset, utilizing transfer learning to adapt pre-trained models, or integrating other neuroimaging modalities (such as MRI) for a comprehensive multimodal analysis.

Finally, the model presents promising real-world applications. It could serve as a decision-support tool for neurologists in clinical settings, facilitating the early detection of dementia, which is crucial for effective treatment planning.

CONCLUSION

The paper concludes that CNNs are a promising tool for detecting dementia using EEG data. Their capability to automatically extract meaningful features from complex brain wave patterns makes them particularly well-suited for this task. While the current study yields encouraging results, further research is essential to validate this approach across larger and more diverse datasets, as well as to assess the model's generalizability in real-world clinical settings. The automated nature of CNN-based analysis has the potential to lead to faster and more reliable diagnoses of dementia, especially in its early stages. However, the effectiveness of these models is contingent upon the quality of the EEG data and the robustness of the CNN architecture. Therefore, additional research is crucial to confirm these findings and ensure the models can perform effectively across varied clinical contexts.

Forthcoming Directions:

- The authors may suggest that future research should focus on enhancing model robustness by testing it on datasets sourced from multiple clinical centers and by utilizing more advanced deep learning architectures
- Discovering explicable AI methods during analysis, where CNNs provide explainable results that clinicians can comprehend, may also have more key area for future work to explore.

REFERENCES

[1] Mehmood A, Yang S, Feng Z, Wang M, Ahmad AS, Khan R, et al. A transfer learning approach for early diagnosis of Alzheimer’s disease on MRI images. Neuroscience. 2021;460:43–52. https://doi.org/10.1016/j.neuroscience.2021.01.002.

[2] https://www.springernature.com/gp/open-research/about/the-fundamentals-of-open-access-and-open-research

[3] Murugan, S., Venkatesan, C., Sumithra, M. G., Gao, X. Z., Elakkiya, B., Akila, M., & Manoharan, S. (2021). DEMNET: A deep learning model for early diagnosis of Alzheimer diseases and dementia from MR images. Ieee Access, 9, 90319-90329.

[4] Kim, M. J., Youn, Y. C., & Paik, J. (2023). Deep learning-based EEG analysis to classify normal, mild cognitive impairment, and dementia: Algorithms and dataset. NeuroImage, 272, 120054.

[5] Sánchez-Reyes, L. M., Rodríguez-Reséndiz, J., Avecilla-Ramírez, G. N., García-Gomar, M. L., & Robles-Ocampo, J. B. (2021). Impact of eeg parameters detecting dementia diseases: A systematic review. IEEE Access, 9, 78060-78074

[6] Leracitano, C., Mammone, N., Hussain, A., & Morabito, F. C. (2020). A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia. Neural Networks, 123, 176-190.

[7] Bi, X., & Wang, H. (2019). Early Alzheimer’s disease diagnosis based on EEG spectral

images using deep learning. Neural Networks, 114, 119-135.
[8] Bharati, P. & Pramanik, A. Deep learning techniques—R-CNN to mask R-CNN: Asurvey. Comput. Intel. Pattern Recogn. Proc. CIPR 2020, 657–668 (2019)
[9] The Alzheimer's Disease Neuroimaging Initiative
(ADNI). https://adni.loni.usc.edu/ (2023).
[10] Stam, C. J., Jelles, B., Achtereekte, H. A. M., Rombouts, S. A. R. B., Slaets, J. P. J., & Keunen, R. W. M. (1995). Investigation of EEG non-linearity in dementia and Parkinson's disease. Electroencephalography and clinical neurophysiology, 95(5), 309-317.
[11] Al-Qazzaz, N. K., Ali, S. H. B. M., Ahmad, S. A., Chellappan, K., Islam, M. S., & Escudero, J. (2014). Role of EEG as biomarker in the early detection and classification of dementia. The Scientific World Journal, 2014(1), 906038.
[12] Dauwels, J., Vialatte, F., & Cichocki, A. (2010). Diagnosis of Alzheimer's disease from EEG signals: where are we standing?. Current Alzheimer Research, 7(6), 487-505.
[13] Babiloni, C., Del Percio, C., Lizio, R., Noce, G., Cordone, S., Lopez, S., ... & Bonanni, L. (2017). Abnormalities of cortical neural synchronization mechanisms in patients with dementia due to Alzheimer's and Lewy body diseases: an EEG study. Neurobiology of aging, 55, 143-158.
[14] Henderson, G., Ifeachor, E., Hudson, N., Goh, C., Outram, N., Wimalaratna, S., ... & Vecchio, F. (2006). Development and assessment of methods for detecting dementia using the human electroencephalogram. IEEE Transactions on Biomedical Engineering, 53(8), 1557-1568.
[15] Bonanni, L., Thomas, A., Tiraboschi, P., Perfetti, B., Varanese, S., & Onofrj, M. (2008). EEG comparisons in early Alzheimer's disease, dementia with Lewy bodies and Parkinson's disease with dementia patients with a 2-year follow-up. Brain, 131(3), 690-705.
[16] Cassani, R., Estarellas, M., San-Martin, R., Fraga, F. J., & Falk, T. H. (2018). Systematic review on resting-state EEG for Alzheimer's disease diagnosis and progression assessment. Disease markers, 2018(1), 5174815.