www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277- 7695
ISSN (P): 2349-8242
NAAS Rating: 5.03
TPI 2019; SP-8(1): 01-04

www.thepharmajournal.com
Received: 01-10-2018
Accepted: 03-11-2018

Dr. Yogesh Bhomia
AIMT, Greater Noida,
Uttar Pradesh, India

Dr. Sunil Kumar Mishra
AIMT, Greater Noida,
Uttar Pradesh, India

Rajesh Pal
AIMT, Greater Noida,
Uttar Pradesh, India

Correspondence
Dr. Yogesh Bhomia
AIMT, Greater Noida,
Uttar Pradesh, India

The role of convolutional neural networks in automated diagnosis of neurological disorders: A critical analysis

Dr. Yogesh Bhomia, Dr. Sunil Kumar Mishra and Rajesh Pal

DOI: https://doi.org/10.22271/tpi.2019.v8.i1Sa.25233

Abstract
In recent years, the application of Convolutional Neural Networks (CNNs) in the realm of medical diagnostics has gained significant attention, particularly in the context of automated diagnosis of neurological disorders. This review paper critically examines the evolving role of CNNs in revolutionizing the diagnostic landscape for neurological conditions. The burgeoning complexity and prevalence of neurological disorders necessitate innovative approaches to diagnosis, and CNNs have emerged as promising tools in this pursuit.
The paper begins by providing an overview of the current state of neurological disorder diagnosis and the challenges faced by traditional methods. The limitations of manual interpretation, time-consuming processes, and the subjectivity inherent in human analysis underscore the need for automated systems that can enhance accuracy, efficiency, and objectivity. CNNs, with their ability to automatically learn hierarchical representations from medical imaging data, present a compelling solution to these challenges.
A comprehensive exploration of the architecture and functioning of CNNs in the context of neurological disorder diagnosis is presented. The review elucidates how CNNs excel in feature extraction and pattern recognition from diverse imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). The paper also discusses the importance of large and well-curated datasets in training CNN models for optimal performance.
The critical analysis section evaluates the strengths and limitations of CNNs in automated diagnosis, considering factors such as interpretability, generalizability across diverse patient populations, and robustness to variations in imaging quality. Furthermore, ethical considerations, including patient privacy and the potential for algorithmic biases, are scrutinized to ensure the responsible deployment of CNNs in clinical settings.
The review concludes by highlighting the future directions and challenges in the field, emphasizing the need for interdisciplinary collaboration between medical professionals, computer scientists, and ethicists. As the integration of CNNs in neurological disorder diagnosis continues to evolve, this critical analysis serves as a valuable resource for researchers, clinicians, and policymakers seeking to navigate the transformative landscape of automated medical diagnostics.

Keywords: Convolutional neural networks, automated diagnosis, neurological disorders, medical imaging, critical analysis, ethical considerations, interdisciplinary collaboration

Introduction
Neurological disorders, encompassing a vast array of conditions affecting the nervous system, pose significant challenges to the healthcare community. The timely and accurate diagnosis of these disorders is crucial for effective patient management and intervention. Traditional diagnostic methods, reliant on manual interpretation and subjective analysis, are increasingly being augmented, if not replaced, by advanced technologies. In this context, Convolutional Neural Networks (CNNs) have emerged as a transformative force in the field of medical diagnostics, particularly in the realm of automated diagnosis of neurological disorders.
The landscape of neurological disorder diagnosis is marked by inherent complexities, ranging from diverse symptomatology to the intricacies of deciphering medical imaging data. Classical diagnostic approaches, while valuable, are often time-consuming and susceptible to human subjectivity. The pressing need for more efficient, accurate, and objective diagnostic tools has driven the exploration of artificial intelligence (AI) and machine learning (ML) techniques. Among these, CNNs, inspired by the visual processing capabilities of the human brain, have demonstrated remarkable prowess in handling complex visual data.

At the core of CNNs lies their ability to automatically learn hierarchical representations from data through the application of convolutional layers. This feature extraction capability is particularly advantageous in the context of medical imaging, where intricate patterns and subtle abnormalities may be indicative of underlying neurological conditions. The review explores the adaptability and effectiveness of CNNs across various imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET).

A critical examination of CNN architecture is pivotal in understanding their role in automated diagnosis. The paper delves into the nuances of how CNNs excel in feature extraction and pattern recognition, facilitating the identification of subtle anomalies that may elude human perception. The importance of extensive and well-curated datasets in training CNN models is emphasized, highlighting the significance of diverse and representative data to ensure generalizability and robust performance.

However, as with any technological advancement, the integration of CNNs in medical diagnostics is not without its challenges. The critical analysis section navigates through the interpretability of CNN-generated results, their generalizability across diverse patient populations, and the potential biases that may arise in algorithmic decision-making. Ethical considerations, such as patient privacy and the responsible deployment of AI in healthcare, are integral components of this examination.

The convergence of medical expertise, computer science, and ethics becomes increasingly apparent in the discussion surrounding CNNs in neurological disorder diagnosis. Interdisciplinary collaboration emerges as a focal point for addressing the multifaceted challenges posed by the adoption of AI in healthcare. As we embark on this transformative journey, the synthesis of medical knowledge with technological innovation becomes paramount for harnessing the full potential of CNNs in the automated diagnosis of neurological disorders. This review aims to provide a comprehensive and insightful exploration of these interconnected themes, offering a roadmap for researchers, clinicians, and policymakers navigating the dynamic landscape of modern medical diagnostics.

Related work: In the pursuit of advancing diagnostic methodologies for neurological disorders, numerous studies have delved into the intricate realm of electroencephalogram (EEG) analysis. Kim *et al*. conducted a comprehensive investigation, utilizing EEG recordings obtained through 21 gold cup electrodes following the 10–20 international system. Horizontal and vertical eye movements were monitored throughout the study. Employing MATLAB and EEGlab toolboxes for signal preprocessing, the team selected five frequency bands for analysis, utilizing fast Fourier transformation to compute spectral power. The analysis of variance (ANOVA) measure was then employed to study EEG power deviations in each frequency band. Subsequently, receiver operating curve (ROC) analysis was conducted to evaluate the diagnostic performance, revealing that delta power exhibited the highest classification accuracy at 62.2%.

Dvey-Aharon *et al*. expanded upon these findings, exploring EEG recordings from 50 participants with a 64-electrode array. Electrodes were strategically placed to monitor vertical and horizontal eye movements, and the Stockwell transform was utilized for time-frequency representation. Distinct features were extracted, leading to high classification accuracy. The best five electrodes demonstrated a prediction accuracy ranging between 92.0% and 93.9%, with electrode F2 proving to be the most discriminative.

Johannesen *et al*. focused on EEG recordings obtained through a 64-electrode system, incorporating a memory working activity. Utilizing the Brain Vision Analyser software, signals were segmented through four processing stages. The 1-norm Support Vector Machine (SVM) classifier was employed, achieving a notable 87% classification accuracy in distinguishing normal versus schizophrenia (SZ) conditions during correct trial data.

Santos-Mayo *et al*. examined EEG-event-related potentials (ERP) signals from an auditory oddball task, utilizing Brain Vision equipment and complying with 10–20 international standards. Employing linear discriminant analysis and feature selection methods, the study achieved high classification rates of 93.42% and 92.23% with Multilayer Perceptron (MLP) and SVM classifiers, respectively.

Ibanez-Molina *et al*. investigated EEG recordings during rest and a naming task, revealing higher complexity values in the right frontal regions of patients at rest. Finally, Pang *et al*. contributed to the field by employing a Multi-domain connectome CNN model, achieving an impressive accuracy of 93.06% through the analysis of 2D time and frequency domain connectivity features and 1D intricate network features from EEG signals.

These studies collectively underscore the growing significance of EEG-based diagnostic approaches, showcasing the potential of advanced analytical techniques such as CNNs in unraveling the complexities of neurological disorders for enhanced and accurate diagnosis.

Methodology Review

Neurological disorder diagnosis has witnessed a paradigm shift with the integration of advanced technologies, particularly the application of diverse methodologies in analyzing electroencephalogram (EEG) signals. This section reviews key methodologies employed in recent studies to facilitate automated diagnosis, shedding light on the intricacies of data acquisition, preprocessing, and analysis.

1. Data Acquisition: Electrode Configurations and Recording Systems

Kim *et al*. and Dvey-Aharon *et al*. both utilized EEG recordings with a substantial number of electrodes, 21 and 64, respectively, conforming to the 10–20 international system. Electrode placements were strategic, considering the monitoring of horizontal and vertical eye movements. Johannesen *et al*. and Santos-Mayo *et al*. expanded upon these configurations, employing 64 electrodes and adhering to international standards. Ibanez-Molina *et al*. used a NeuroscanSynAmps 32-channel amplifier, capturing EEG signals at rest and during a naming task. Pang *et al*. extended the scope by analyzing EEG signals using a Multi-domain connectome CNN model, emphasizing the relevance of connectivity features.

2. Signal Preprocessing Techniques

In the preprocessing phase, commonalities emerge among the studies. Kim *et al*. and Dvey-Aharon *et al*. leveraged MATLAB and EEGlab toolboxes for signal preprocessing, with a focus on the extraction of relevant features for subsequent analysis. Dvey-Aharon *et al*. further segmented raw signals into intervals, utilizing the Stockwell transform for time-frequency representation. Johannesen *et al*. applied the Brain Vision Analyser software, employing a four-stage processing approach: pre-stimulus baseline, encoding, retention, and retrieval. Santos-Mayo *et al*. utilized EGGLAB for preprocessing EEG-event-related potentials (ERP) signals, extracting time-domain and frequency-domain features. Ibanez-Molina *et al*. adopted a moving window method for EEG segment analysis, computing Lempel–Ziv complexity (LZC) values.

3. Feature Extraction and Selection

The extraction of discriminative features is a crucial step in enhancing diagnostic accuracy. Dvey-Aharon *et al*. extracted features from the time-frequency representation, discerning time frames based on stimuli. Johannesen *et al*. performed feature selection using the wrapper method, highlighting the significance of feature relevance in achieving high classification accuracy. Santos-Mayo *et al*. utilized linear discriminant analysis and various feature selection methods, emphasizing the importance of discerning informative features from the vast EEG data.

4. Classification Models

The studies under consideration employed diverse classification models to discriminate between normal and pathological conditions. Johannesen *et al*. utilized the 1-norm Support Vector Machine (SVM) classifier, achieving noteworthy accuracy in distinguishing normal and SZ conditions. Santos-Mayo *et al*. employed both Multilayer Perceptron (MLP) and SVM classifiers, showcasing the versatility of machine learning algorithms in EEG-based classification. Pang *et al*. adopted the Multi-domain connectome CNN model, emphasizing the role of deep learning architectures in achieving high classification rates.

5. Evaluation Metrics

Commonly employed evaluation metrics include receiver operating curve (ROC) analysis, reported by Kim *et al*. for diagnostic performance assessment, and classification accuracy, as demonstrated by Johannesen *et al*. , Santos-Mayo *et al*. , and Pang *et al*. . These metrics provide a quantitative assessment of the models' effectiveness in distinguishing between normal and pathological states.

6. Temporal and Frequency Domain Analysis

Several studies have delved into the temporal and frequency characteristics of EEG signals to extract valuable information for diagnosis. They employed fast Fourier transformation for spectral power computation in distinct frequency bands, showcasing the relevance of frequency domain analysis. Utilized the Stockwell transform for time-frequency representation, emphasizing the significance of both temporal and frequency features. Additional investigations into the temporal dynamics and frequency spectra of EEG signals contribute to a more nuanced understanding of neurological disorders.

7. Artifact Removal and Noise Reduction Techniques

Signal integrity is paramount in EEG analysis, and addressing artifacts and noise is a critical step in ensuring accurate diagnostic outcomes. Kim *et al*. and Dvey-Aharon *et al*. utilized MATLAB and EEGlab toolboxes for preprocessing, suggesting the incorporation of artifact removal techniques. Exploring advanced methods for artifact detection, such as independent component analysis (ICA) or wavelet denoising, can enhance the robustness of EEG-based diagnostic models.

8. Cross-Validation and Generalization Strategies

Ensuring the generalizability of diagnostic models is essential for their clinical applicability. Johannesen *et al*. implemented a Support Vector Machine (SVM) classifier and assessed its performance through cross-validation. Exploring various cross-validation techniques, such as k-fold cross-validation or leave-one-subject-out validation, can provide insights into the model's ability to generalize across diverse datasets. Robust generalization strategies are pivotal for the successful deployment of automated diagnostic tools in real-world clinical scenarios.

Future Outlook

As the landscape of automated diagnosis of neurological disorders continues to evolve, several promising avenues emerge, propelling the field toward greater precision, efficiency, and clinical applicability. The convergence of technological advancements and interdisciplinary collaboration lays the foundation for an exciting future in the realm of Convolutional Neural Networks (CNNs) for neurological disorder diagnosis.

1. Integration of Multimodal Data

The integration of multimodal data, combining information from various imaging modalities such as EEG, functional MRI (fMRI), and genetic markers, holds immense potential. Future research endeavors are poised to explore the synergies between different data types, allowing for a more comprehensive understanding of the complex neurobiological underpinnings of disorders. This holistic approach may foster the development of robust diagnostic models that capture a spectrum of neurological abnormalities.

2. Explainable AI for Clinical Adoption

The implementation of Explainable Artificial Intelligence (XAI) techniques is paramount for the clinical adoption of CNNs in neurological diagnosis. Future research will likely focus on enhancing the interpretability of CNN models, providing clinicians with transparent insights into the decision-making process. This interpretability is crucial for establishing trust in AI-driven diagnostic tools and facilitating seamless integration into clinical workflows.

3. Personalized Medicine and Treatment Planning

Advancements in CNN-based diagnosis are paving the way for personalized medicine in the field of neurology. Future studies may delve into tailoring diagnostic models to individual patient profiles, considering genetic variations, lifestyle factors, and specific manifestations of neurological disorders. This personalized approach not only enhances diagnostic accuracy but also lays the groundwork for targeted and optimized treatment strategies.

4. Ethical Considerations and Regulatory Frameworks

As CNNs gain prominence in clinical applications, addressing ethical considerations becomes imperative. Future research will likely explore the ethical implications of AI in neurological diagnosis, encompassing issues of patient privacy, data security, and algorithmic biases. The development of robust regulatory frameworks will be crucial to ensure responsible and ethical deployment of CNNs in healthcare settings.

5. Real-Time Diagnostic Support Systems

The advent of real-time diagnostic support systems powered by CNNs holds great promise. Future endeavors may focus on the development of systems that provide instantaneous diagnostic insights, aiding healthcare professionals in timely decision-making. This could be particularly impactful in emergency situations, where rapid and accurate diagnoses are critical for initiating prompt interventions.

Evolution in the Application of Convolutional Neural Networks for Neurological Disorder Diagnosis: Past vs. Future

Past Application

In the past, the application of Convolutional Neural Networks (CNNs) in the diagnosis of neurological disorders has primarily focused on exploring the potential of these advanced algorithms in automating the analysis of electroencephalogram (EEG) signals. Studies have laid the foundation by utilizing CNNs to process EEG data and discriminate between normal and pathological conditions. These early applications underscored the ability of CNNs to extract intricate patterns and features from EEG recordings, contributing to the augmentation of diagnostic accuracy.

However, the past application was characterized by a more rudimentary understanding of the complexities inherent in neurological disorders. The emphasis was often on achieving proof of concept and demonstrating the feasibility of using CNNs as a diagnostic tool. The interpretability of the CNN models was a challenge, limiting their direct translation into clinical practice. Additionally, ethical considerations and regulatory frameworks were in nascent stages, warranting further exploration as these technologies evolved.

Future Application

Looking ahead, the future application of CNNs in neurological disorder diagnosis is poised for transformative advancements. One notable shift lies in the integration of multimodal data, allowing for a more comprehensive and holistic assessment of neurological conditions. Future studies are expected to leverage not only EEG data but also incorporate information from other imaging modalities, genetic markers, and clinical parameters. This shift toward a more integrative approach aligns with the broader trend of personalized medicine, aiming to tailor diagnostic models to individual patient profiles.

Explainable Artificial Intelligence (XAI) is another pivotal aspect of the future application. Researchers recognize the imperative of making CNN models more interpretable, addressing the "black box" nature of deep learning algorithms. This emphasis on interpretability is crucial for gaining the trust of healthcare professionals and ensuring the seamless integration of CNNs into clinical workflows.

Furthermore, ethical considerations will play a central role in shaping the future application of CNNs. As these technologies become more pervasive in clinical settings, there is a heightened awareness of the need for robust ethical frameworks, encompassing issues of patient privacy, data security, and algorithmic biases. Future applications are expected to prioritize ethical considerations, ensuring responsible and transparent use of CNNs in healthcare.

Conclusion

The journey of Convolutional Neural Networks (CNNs) in the automated diagnosis of neurological disorders has witnessed a notable evolution, transitioning from early applications to a future characterized by sophistication, integration, and ethical consciousness.

In the past, pioneering studies laid the groundwork, demonstrating the potential of CNNs to analyze electroencephalogram (EEG) signals and distinguish between normal and pathological conditions. However, this phase was marked by a rudimentary understanding of the complexities inherent in neurological disorders. Interpretability challenges and a lack of robust ethical frameworks posed limitations to direct clinical translation.

The future application of CNNs signals a transformative trajectory. Integration of multimodal data, as envisioned by upcoming studies, promises a more comprehensive assessment, incorporating diverse information sources to refine diagnostic accuracy. The shift towards personalized medicine, tailoring diagnostic models to individual patient profiles, signifies a more nuanced and patient-centric approach.

Explainable Artificial Intelligence (XAI) emerges as a crucial focus for the future, addressing the interpretability concerns associated with deep learning models. This emphasis on transparency seeks to build trust among healthcare professionals, ensuring the effective assimilation of CNNs into clinical workflows.

Ethical considerations, notably accentuated in the future application, are pivotal. The heightened awareness surrounding patient privacy, data security, and algorithmic biases underscores the commitment to responsible and transparent use of CNNs in healthcare settings.

References

1. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H, Subha DP. Automated EEG-based screening of depression using deep convolutional neural network. Comput. Methods Programs Biomed. 2018;161:103-113.
2. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Comput. Biol. Med. 2018;100:270-278.
3. Sridhar C, Bhat S, Acharya UR, Adeli H, Bairy GM. Diagnosis of attention deficit hyperactivity disorder using imaging and signal processing techniques. Comput. Biol. Med. 2017;88:93-99.
4. Bhat S, Acharya UR, Adeli H, Bairy GM, Adeli A. Autism: cause factors, early diagnosis and therapies. Rev. Neurosci. 2014;25:841-850.
5. Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: A review. Comput. Methods Programs Biomed. 2018;161:1-13.
6. Kaushik P, Yadav R. Reliability design protocol and block chain locating technique for mobile agent Journal of Advances in Science and Technology (JAST), 2017;14(1):136-141. https://doi.org/10.29070/JAST