Application of Artificial Intelligence in Image Processing of Neurodegenerative Disorders: A Review Study

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Abstract

Neurodegenerative diseases can make life difficult and lead to death in many cases. They also can be difficult, time-consuming, and costly to diagnose with enough accuracy/certainty. Artificial intelligence (AI) has shown promise in tackling some of the challenges present in medical imaging and is anticipated to become a crucial tool in health care applications in the near future. In particular, deep learning methods have displayed great performance in various subfields of image processing, including but not limited to image segmentation, image synthesis, and image reconstruction. In this paper, many state-of-the-art applications of deep learning models in image processing were reviewed.

Keywords: Artificial Intelligence, Deep Learning, Medical Imaging, Neurodegenerative Diseases

1. Background

Neurological disorders take a heavy toll on public health. The Global Burden of Diseases (2010) classified the following diseases as neurological disorders: Alzheimer's disease (AD, also known as dementia), Parkinson's disease (PD), multiple sclerosis (MS), epilepsy, migraine, and tension-type headache (TTH) (1). Neurodegenerative diseases, a class of neurological disorders, occur when the neurons of the central nervous system get damaged or die as a result of the disease, leading to severe disabilities of the individual and, ultimately, their death. Neurodegenerative diseases affect millions of people worldwide but are mainly reported in the elderly. Health care professionals, such as radiologists and clinicians, must carry out a detailed interpretation of magnetic resonance imaging (MRI) in clinical practice. However, due to the large number of MRIs, interpretations are time-consuming and easily affected by human experts' biases and potential fatigue. As a result, beginning in the early 1980s, doctors and researchers began to use computer-assisted diagnosis (CAD) structures to analyze medical images and boost their effectiveness (2).

Early detection and treatment of neurodegenerative diseases can significantly slow their development. Computational approaches aimed at diagnosing and monitoring respective diseases and CAD systems can significantly assist in increasing the chance of survival. They are also capable of extracting important features describing patterns from the data and subsequently play a key role in medical image analysis (2-4). Recent advances in artificial intelligence (AI) can be a major help in achieving the aforementioned goals. Artificial intelligence can automate image analysis and plays a major role in diagnosing and examining these diseases, allowing doctors to make fast and accurate treatment recommendations (5).

The progressive loss of the structure/functionality of neurons or neurodegeneration is the root cause of neurodegenerative diseases. Cell death may result from such neuronal injury. Neurodegeneration in the nervous system can be observed in various scales, ranging from molecular abnormalities to systemic failures. These illnesses are incurable because there is no known way

of stopping progressive degeneration; however, early diagnosis and treatment of neurodegenerative diseases can significantly slow their progression (6, 7).

Alzheimer's disease is the most widely observed neurodegenerative disease, accounting for 60% - 70% of dementia cases. Its symptoms are linked to a steady decline in brain function. It can impair memory, reasoning, and other mental abilities and is currently impossible to cure. The protein fragment β-amyloid (which builds up as plaques outside of neurons in the brain) and twisted tau protein strands (which form tangles inside neurons) are some of its pathological characteristics (8). Several studies have also found an accumulation of alpha-synuclein or Lewy-related pathology in more than 50% of post-mortem examinations of AD brains (9).

The second most common neurodegenerative disease is PD. it is a chronic condition that affects both the nervous system and the body parts that are under the control of the nervous system. The symptoms appear gradually, and the most common of them is tremors. The disorder can also cause the slowing or general difficulty of movement. The buildup of misfolded alpha-synuclein and the degeneration of dopaminergic neurons in the substantia nigra are 2 significant characteristics of PD. This disrupts signal transduction pathways in the brain, resulting in PD symptoms. As the condition worsens, alpha-synuclein misfolding and accumulation, abnormal dopamine metabolism, oxidative stress, and neuronal death emphasize one another (10).

The central nervous system disease known as MS is a long-term, inflammatory, demyelinating condition. It is a common root of neurological disability in young adults. Multiple sclerosis is a diverse, multifactorial, immune-mediated illness brought on by intricate gene-environment interactions. Demyelinating lesions that develop over time in the white matter and grey matter of the brain and spinal cord are the pathological hallmarks of MS (11).

Today, diagnostic imaging is a helpful resource in medicine. Magnetic resonance imaging, positron emission tomography (PET), and other imaging modalities are useful for noninvasively mapping a subject's anatomical brain structure. These technologies have significantly increased medical and scientific knowledge of normal and malignant anatomy and are essential in diagnosis and treatment planning. Advancements in medical imaging provided various imaging modalities to detect and diagnose neurodegenerative diseases (12).

Magnetic resonance imaging is an imaging technique that generates images by observing the behavior of atomic nuclei with non-zero spins in a strong magnetic field (10). Currently, T1- and T2-weighted images are the most

used MRI sequences available. T1-weighted scans are obtained using the short echo time (TE) and repetition time (TR) recorded. The main determining factors of the image's brightness and contrast are the T1 properties of the imaged tissue. T2-weighted images, on the other hand, are generated from longer TE and TR (13).

Positron emission tomography is another imaging technique. It is a nuclear imaging technique that relies on the decay characteristics of positron-emitting radionuclides, such as fluorine-18 (18F, t1/2 = 109 min), carbon-11 (11C, t1/2 = 20 min), or oxygen-15 (15O, t1/2 = 2 min). The PET imaging of beta-amyloid plaques will significantly improve the diagnosis of AD (10, 14). Positron emission tomography is a noninvasive in vivo imaging technique that can measure target expression and drug occupancies in the presence of a suitable tracer. As a result, scientists from all over the world have been working to create innovative α-syn PET tracers that will revolutionize imaging techniques for neurodegenerative disorders (15).

The exponentially increasing flow of data opened the door to a new era of AI algorithms in every technological endeavor, including medicine and radiology. However, the current success of AI in a few elevated applications has obscured decades of advances in the development of computational technology for medical image processing (16).

2. Objectives

AI and, in particular, techniques like deep learning have recently produced outstanding results with "big data" in many diverse domains by reaping the benefits of the ever-increasing quantity of labeled digital data available in every area of technological activity (17). Deep learning uncovers informative representations automatically without the technical understanding of domain experts, allowing non-experts to utilize the deep learning-based techniques effectively. As a result, deep learning has rapidly become a preferred methodology for medical image analysis in recent decades (17, 18). Thus, in this review, we went over the 3 important and frequently used techniques: Classification, image segmentation, and image generation.

3. Methods

3.1. Classification

The most common learning method in AI-based applications is supervised learning, in which the classification model is trained by presenting labeled training data to the model. The learning system's task is

then to find a relationship that maps each input of the training sample into an output (the label). In medical science, input often includes medical images, while the output can be anything from the diagnosis of a disease to a patient's condition (19). A feature extraction step is often done before the training phase to speed up the training and improve accuracy. Ahmed et al. suggested using biomarkers derived from images to identify AD and mild cognitive impairment (20). They extracted visual features from structural MRI to differentiate and classify Alzheimer's and mild cognitive impairment patients (20).

Automated gait deficit diagnosis and severity were made possible by AI across several symptomatic stages of PD. Varrecchia et al. discovered a small number of features that differentiates PD from healthy control and distinguishes gait patterns between different Hoehn and Yahr stages (21, 22).

3.2. Image Segmentation

Image segmentation is to partition an image into mutually exclusive regions that are homogeneous in some way, such as intensity or texture (23). Although atrophy is the most common biomarker used to diagnose epilepsy, a recent study has shown that cerebral gray matter atrophy can also be seen on structural MRI in neurodegenerative diseases (24). It has been discovered to correlate with the neurodegenerative mechanisms that underlie the cognitive impairment caused by PD (25).

A deep learning algorithm, called "DeepnCCA," was created by Platten et al. and is tailored to normalize the segmentation of the corpus callosum in MS patients (26). Its output was highly comparable to traditional manual segmentations. Further shape analysis revealed a correlation between a thinner and more angular corpus callosum and a higher level of clinical disability (26). Similar to previous research, Brusini et al. presented a completely automated deep learning-based corpus callosum segmentation tool designed and developed for modern MS imaging with clinical correlations similar to computationally intensive alternatives (27). They utilized U-Net architectures to automatically segment the corpus callosum from a single midsagittal slice input (28).

To diagnose and follow several clinical conditions, including AD, the segmentation of the hippocampus (HC) in MRI is a crucial step. Liu and Yan proposed a semi-automatic model by combining a deep belief network and the lattice Boltzmann method (29). Coronado et al. trained and assessed a 3D convolutional neural network to segment gadolinium-enhancing lesions using a sizable cohort of MRI data from patients with MS (30). An extensive dataset evaluation revealed excellent performance, with a high segmentation accuracy measured by the Dice similarity score of 0.77 (30).

3.3. Image Generation

Following the bloom of deep learning in the early 2010s, meaningful advances in generative models were made. Such models are mainly developed to synthesize parts of or the whole of images that had not existed prior to the synthetization or were not available in high resolution. One well-known generative model that has been the focus of much attention since its introduction in 2016 is a generative adversarial network. The medical applications of such generative models can be classified into 3 main categories: Modality transformation, image reconstruction, and super-resolution (18).

Due to the advantages and challenges of each imaging method available today, no particular method perfectly fits all the experiment requirements. One example of this trade-off of advantages and disadvantages is the high spatial resolution attainable by functional MRI (fMRI) while lacking temporal resolution (31). To address this trade-off, there have been attempts at the modality transformation of medical images: Transforming the images obtained by one imaging modality to another. The feasibility of reaching useful modality transformation (or image translation, as in some resources) depends upon the chosen initial and target modalities, as well as the availability of sufficient data of adequate quality. One example of a possibly useful transformation is using MRI to generate synthesized computed tomography (CT) images (32). A noteworthy recent work conducted in this line of research is a study where the end goal was to synthesize PET images from MR images to diagnose different AD stages (33). This task was done using a novel 3D self-attention conditional GAN (SCGAN) trained on the ADNI3 data. The synthetic PET images were reported to be the most similar to the corresponding real images compared with many other alternative generative architectures, both qualitatively and based on 3 chosen metrics (i.e., normalized root-mean-squared error, peak signal-to-noise ratio, and structural similarity). Despite being similar to real images, the synthesized PET images reportedly generally lacked the necessary information to accurately determine the AD stage (34).

As a result of the various sources of noise present in most brain imaging methods, parts (or all) of recorded medical images are prone to be of inadequate quality and, therefore, not useful in diagnosis tasks. In the cases of images with noisy or missing sections, image reconstruction can be used to obtain usable images containing all essential sections. A recent example of published work in the field of image reconstruction is

done by Korkmaz et al., which used generative vision transformers to reconstruct MR images (35).

To make low-resolution images useful, attempts at improving the resolution have been made under the term "Super Resolution," where the model typically receives a low-resolution input image and outputs the same image in a higher resolution. The previously introduced SCGAN model was also used for super-resolution tasks, which was reported successful (33). A useful application of such models is speeding up and lowering imaging costs, as the quality can be improved later using these models (36).

4. Conclusions

In this review, we explored and investigated some of the novel AI algorithms and state-of-the-art deep neural networks for the monitoring and disorder diagnosis of medical images of patients, with a strong emphasis on the 3 most common neurodegenerative disorders: AD, PD, and MS. Numerous brain microstructural changes in neurodegenerative patients have already been detected during the past decade. We demonstrated the advantages of deep learning methods and their feasibility in improving clinical practice in the literature. Deep learning is the case for some of the papers cited in this manuscript, including evidence for applying the U-Net model for corpus callosum segmentation or Generative adversarial networks for image synthesis and reconstruction.

Footnotes

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