COMPARISON OF ANATOMICAL AND DIFFUSION MRI FOR DETECTING PARKINSON'S DISEASE USING DEEP CONVOLUTIONAL NEURAL NETWORK

Although tests on more diverse data are warranted, deep-learned models from dMRI show promise for PD classification, and supports the use of diffusion-weighted images as an alternative to anatomical images for AI-based detection of Parkinson's disease.

Parkinson's disease (PD) is a progressive neurodegenerative disease that affects over 10 million people worldwide. Brain atrophy and microstructural abnormalities tend to be more subtle in PD than in other age-related conditions such as Alzheimer's disease, so there is interest in how well machine learning methods can detect PD in radiological scans. Deep learning models based on convolutional neural networks (CNNs) can automatically distil diagnostically useful features from raw MRI scans, but most CNN-based deep learning models have only been tested on T1-weighted brain MRI. Here we examine the added value of diffusion-weighted MRI (dMRI) - a variant of MRI, sensitive to microstructural tissue properties - as an additional input in CNN-based models for PD classification. Our evaluations used data from 3 separate cohorts - from Chang Gung University, the University of Pennsylvania, and the PPMI dataset. We trained CNNs on various combinations of these cohorts to find the best predictive model. Although tests on more diverse data are warranted, deep-learned models from dMRI show promise for PD classification. Clinical Relevance This study supports the use of diffusion-weighted images as an alternative to anatomical images for AI-based detection of Parkinson's disease.

PRE-TRAINED DEEP LEARNING MODELS FOR BRAIN MRI IMAGE CLASSIFICATION

Validation of the test set utilizing accuracy, recall, Precision, and F1 score showed that the pre-trained VGG-19 model with transfer learning exhibited the best performance.

Brain tumors are serious conditions caused by uncontrolled and abnormal cell division. Tumors can have devastating implications if not accurately and promptly detected. Magnetic resonance imaging (MRI) is one of the methods frequently used to detect brain tumors owing to its excellent resolution. In the past few decades, substantial research has been conducted in the field of classifying brain images, ranging from traditional methods to deep-learning techniques such as convolutional neural networks (CNN). To accomplish classification, machine-learning methods require manually created features. In contrast, CNN achieves classification by extracting visual features from unprocessed images. The size of the training dataset had a significant impact on the features that CNN extracts. The CNN tends to overfit when its size is small. Deep CNNs (DCNN) with transfer learning have therefore been developed. The aim of this work was to investigate the brain MR image categorization potential of pre-trained DCNN VGG-19, VGG-16, ResNet50, and Inception V3 models using data augmentation and transfer learning techniques. Validation of the test set utilizing accuracy, recall, Precision, and F1 score showed that the pre-trained VGG-19 model with transfer learning exhibited the best performance. In addition, these methods offer an end-to-end classification of raw images without the need for manual attribute extraction.