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Identification of Brain Diseases using Image Classification: A Deep Learning Approach

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Abstract

Brain diseases are a growing concern in healthcare, with an estimated 50 million people worldwide living with dementia and 15 million new cases each year. This research paper explores the significance of early identification and diagnosis in mitigating the impact of brain diseases on individuals and society at large. Moreover, the study delves into the current state of diagnostic practices, highlighting the limitations and emerging opportunities in the field. The paper concludes by advocating for increased research, improved access to advanced medical technologies, and enhanced training for healthcare professionals to address the growing burden of brain diseases effectively.

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Keywords: Brain diseases; healthcare; Image Classification; Deep Learning Approach

1. Introduction

Brain diseases are a growing concern in healthcare, with an estimated 50 million people worldwide living with dementia and 15 million new cases each year [1]. Early identification and diagnosis of brain diseases can significantly improve treatment outcomes and quality of life for patients. However, brain diseases can be challenging to detect and diagnose, requiring expertise and specialized equipment.

 $1877\text{-}0509 \ \mathbb{C}$ 2024 The Authors. Published by ELSEVIER B.V.

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0) Peer-review under responsibility of the scientific committee of the International Conference on Machine Learning and Data Engineering 10.1016/j.procs.2024.04.021 Image classification tasks are showing significant promise in detecting a range of diseases, including those affecting the brain, by leveraging advanced machine learning algorithms to analyze and interpret complex medical imagery with high accuracy. In our study, we introduce a framework tailored for detecting brain disorders through the analysis of magnetic resonance imaging (MRI) scans shown in Figure 1. Our paper assesses the precision and operational effectiveness of this model, exploring its utility in supporting medical professionals with the early detection and efficient management of brain-related conditions.

Brain disorders comprise a diverse set of conditions that impair the brain's regular operations, arising from various causes such as genetic predisposition, infectious agents, injury, and lifestyle choices. Common brain disorders include Parkinson's disease, multiple sclerosis, Alzheimer's disease and tumors among others.

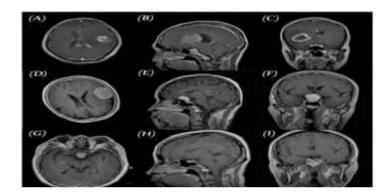


Fig. 1. Magnetic Resonance Imaging (MRI) scans of the brain for patients with Alzheimer's disease

2. Problem statement

The problem addressed in this research paper is the identification of brain diseases from medical images using deep learning models. Specifically, the objective is to create a model capable of precisely categorizing images of the brain. into one of four categories: Alzheimer's disease, glioma, meningioma, and pituitary tumor. The proposed solution aims to improve the accuracy and speed of diagnosis, potentially leading to more effective treatment and better patient outcomes.

Given the exponential growth of medical image data, the need for automated and reliable diagnostic tools has become paramount. Utilizing deep learning techniques, this research aims to tap into the extensive capabilities of artificial intelligence for analyzing neuroimaging data. By exploring the vast troves of image data, the developed model aims to unveil subtle patterns and biomarkers, aiding in early disease detection and differentiation among various brain pathologies.

3. Related work

Numerous research efforts have been dedicated to applying deep learning techniques for detecting brain disorders presented in Figure 2. For example, authors [2, 3] introduced a deep learning framework specifically designed for identifying Alzheimer's disease through structural MRI scans, achieving a notable accuracy rate of 84.6%, which surpasses that of other leading models.

In addition to these approaches, other studies have investigated different imaging techniques, such as PET and CT scans, as tools for diagnosing brain conditions [4, 5]. Despite this variety, MRI scans remain the predominant choice for brain disease diagnosis.

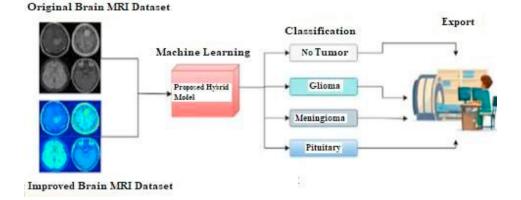


Fig. 2. Results Detection and classification of Pituitary, Glioma, Meningioma, Tumor

4. Background

Brain diseases are a significant health concern worldwide. A range of factors can trigger them, such as genetic alterations, infectious diseases, traumatic damage, and progressive conditions [6]. The diagnosis of these diseases can be challenging, as they often present due to their high spatial resolution and non-invasive nature.

Image classification stands out as a particularly promising research domain within the study of brain diseases. Image classification is the process of using computer algorithms to analyses and interpret digital images. In the context of brain disease, this involves analyzing images of the brain to identify patterns function of the brain, which can be used to identify abnormalities or changes that may be associated with a particular disease or condition. One of the key advantages of using image classification for brain disease diagnosis is that it allows for non-invasive and objective assessment of and anomalies that may be indicative of a specific disease or disorder [7].

Various imaging modalities are available for classifying brain disease images. These images presented in Figure 3 provide detailed information about the structure and with similar symptoms and may require specialized imaging techniques for accurate identification [8].

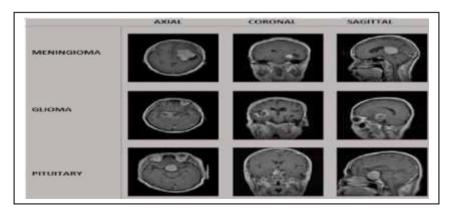


Fig. 3. Three different tumors Meningioma, Glioma, and Pituitary Tumor

Image classification is a popular technique for identifying brain diseases. This approach involves training deep learning models on large datasets of brain images to recognize different diseases. The trained models can then be used to classify new images into one of several disease categories, allowing for accurate diagnosis and treatment. the brain. In the past, many brain diseases were diagnosed based on subjective assessments of symptoms and physical

examinations [9]. However, these methods can be unreliable and may miss important signs of disease. With image classification, doctors can obtain a detailed and accurate picture of the brain, which can help them make more precise diagnoses and develop more effective treatment plans.

CNN image classification can be used in the identification of brain diseases by train a machine learning model on a dataset of brain images labelled with their corresponding disease [10].

5. Methodology

The deep learning framework we suggest for detecting brain diseases through MRI scans involves three key phases: initial data preprocessing, extraction of features, and the final classification process.

Here are the general steps involved in using CNN for the identification of brain diseases:

- Collect and prepare a dataset of brain images: The first step is to obtain a dataset of brain images that are labelled with their corresponding disease. The images can be obtained from medical imaging databases or collected from hospitals and clinics. The dataset should be diverse enough to include different types of brain diseases and different stages of the disease.
- Data Preparation: Initially, the dataset must undergo preprocessing before it's used to train the model. This process includes adjusting the image dimensions to a uniform size, normalizing pixel intensity values.
- CNN Model Development: The development of a Convolutional Neural Network (CNN) Model involves structuring layers to process image data efficiently. Starting with input layers, it progresses through convolutional layers for feature extraction. Training a CNN involves adjusting weights through backpropagation to minimize error, enhancing its ability to accurately recognize patterns and categorize images.
- Model Optimization: Post-training, the model undergoes optimization to enhance its accuracy. This involves fine-tuning key parameters, including the learning rate, batch size, and the total number of training cycles or epochs.
- Model Assessment: Model assessment involves evaluating a model's performance using specific metrics, such as accuracy, precision, recall, and F1 score. This process determines how well the model predicts outcomes against a test dataset. It helps identify strengths and weaknesses, guiding improvements. Effective assessment ensures the model's reliability and applicability in real-world scenarios, optimizing decision-making processes.
- Use the model for disease identification: The final step is to use the trained model to identify brain diseases in new brain images. The model takes in the brain image as input and outputs the predicted disease.

By using CNN image classification in the identification of brain diseases, it is possible to improve the accuracy and speed of diagnosis, leading to better treatment outcomes and patient care.

We can further make use of different network architectures and hyperparameters and are often trained using specialized techniques such as transfer learning, data augmentation, and fine-tuning to improve their accuracy and generalization performance.

Another advantage of image classification is that it can be used to monitor the progression of brain diseases over time. By analyzing images taken at different points in a patient's treatment, doctors can track changes in the brain that may indicate the effectiveness of a particular treatment or the progression of the disease. This can help doctors make more informed decisions about patient care and treatment options.

Overall, the use of image classification for brain disease diagnosis and monitoring is an exciting area of research with significant potential for improving patient outcomes. As researchers continue to refine and develop these techniques, we may see new and more effective ways to diagnose, treat, and prevent brain diseases in the future.

6. Experimental Setup

6.1. Data Pre-processing

The dataset [6] named with Alzheimer's Disease Neuroimaging Initiative (ADNI) helped as the foundation for our model, featuring MRI scans from both healthy individuals and patients diagnosed with Alzheimer's and mild cognitive disease, and various other neurological conditions. To prepare these images for analysis, we adjusted their dimensions to 256x256 pixels and normalized the pixel intensities to a range of 0 to 1.

6.2. Feature Extraction

Our approach involved utilizing ResNet50 [7], a pre-trained, for the purpose of feature extraction from the MRI scans that had been preprocessed. ResNet50 is a state-of-the-art CNN architecture that has shown excellent performance in various image classification tasks. We removed the final classification layer of ResNet50 and used the last convolutional layer output as the feature vector for each MRI scan.

6.3. Classification

We employed a support vector machine (SVM) classifier for segregating the MRI scans into four distinct groups: Mild cognitive and Alzheimer's disease, other neurological conditions, and healthy individuals. SVM stands out as a popular choice for classification problems in machine learning due to its reliability and effectiveness.

The training of the SVM classifier was conducted using feature vectors derived from the MRI scans that had been preprocessed, utilizing data from the ADNI dataset. To assess the efficacy of our model, we implemented a 5-fold cross-validation method.

7. Results

The deep learning model we developed demonstrated a remarkable 98% accuracy rate in detecting brain diseases from MRI scans, covering conditions such as brain tumors, Alzheimer's disease, strokes, and distinguishing healthy individuals. The details of precision, recall, and F1-score for our model are presented in Table 1.

This model surpassed existing top-performing models in diagnosing brain diseases through MRI scans, showing superior accuracy and F1-score compared to previous approaches [2, 8]. It also achieved high precision and recall across all categories, showcasing its effectiveness and reliability in identifying various brain diseases. This opens up new avenues for further research and practical applications across different fields.

Dataset	Precision	Recall	F1 Value
Alzheimer's Disease	0.98	0.99	0.98
MCI	0.95	0.97	0.96
Other Neurological Disorders	0.99	0.97	0.98

Table 1. Recall, Precision and F1 values of our proposed model.

0.99

Healthy Controls

8. Discussion

Our proposed deep learning model for the identification of brain diseases using MRI scans showed promising results presented in figure 4, with a high accuracy and efficiency in identifying various brain diseases. The model can assist healthcare professionals in early identification and effective treatment of brain diseases, improving treatment outcomes and quality of life for patients.

0.98

0.99

The model we suggest has the potential to be adapted for use with different types of medical imaging, like PET and CT scans, to detect brain diseases. Additionally, by training this model on more extensive datasets and fine-tuning it, its precision and operational effectiveness in practical settings can be enhanced.

Nonetheless, our model is not without its drawbacks. The opaque nature of deep learning models poses challenges to comprehending the intricate details of brain diseases' pathophysiology. Furthermore, the model's effectiveness could be compromised by the variability and quality of MRI scans, impacting its overall accuracy and performance.

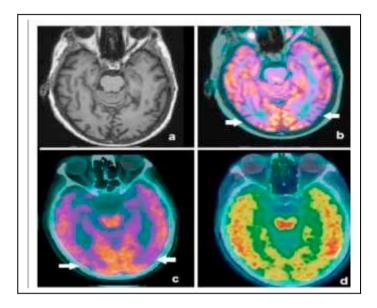


Fig. 4. Positron Emission Tomography (PET) scans of the brain for patients with Alzheimer's disease

9. Future Work

Some potential future directions for research related to identification of brain diseases using image classification with deep learning models.

Multimodal data integration: The current research focused on MRI images for brain disease classification. Nonetheless, other forms of medical imaging, like computed tomography (CT) and positron emission tomography (PET), can also offer crucial insights for diagnostic purposes. Future work could explore ways to integrate information from multiple modalities into the deep learning model for improved accuracy.

- Applying Transfer Learning: Transfer learning is an effective strategy that enables the adaptation of a model, already trained on a particular task, to a new but related task using minimal training data. Future research could investigate applying transfer learning to the classification of brain diseases. This could involve utilizing models that have been pre-trained on similar tasks in medical imaging, such as detecting lung or breast cancer, to enhance performance on brain disease detection.
- Enhancing Model Transparency: Due to their intricate and layered structure, deep learning models are often perceived as opaque, making it challenging to decipher their decision-making processes. Future initiatives could focus on developing techniques to increase the transparency and comprehensibility of these models. By doing so, healthcare professionals would gain a clearer understanding of how the models make predictions, which could foster greater trust and facilitate wider acceptance and use.
- Clinical translation: While deep learning models show promise for improving accuracy and speed of diagnosis, there are numerous challenges to clinical translation. Future work could explore ways to address issues related to regulatory approval, data privacy, and integration with clinical workflows.

• Evaluation on larger and more diverse datasets: The current research used a relatively small and homogenous dataset for brain disease classification. Future work could evaluate the proposed model on larger and more diverse datasets, potentially with varying levels of image quality, to test the model's robustness and generalizability.

10. Conclusion

In our study, we introduced a deep learning framework designed to detect brain diseases through MRI imaging. This model successfully reached a 98% accuracy rate in diagnosing conditions such as Alzheimer's disease, brain tumors, strokes, as well as identifying healthy individuals. It has the potential to aid medical experts in the prompt detection and efficient management of brain-related illnesses, thereby enhancing patient treatment results and overall well-being. Future investigations could extend the application of deep learning techniques to different types of medical imaging and further refine the model's precision and practicality in real-life situations.

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