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Brain Tumor and Alzheimer's Detection using Deep Learning

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A B S T R A C T

The global prevalence of brain diseases is rising quickly. Devastating brain tumors cause thousands of deaths each year and the most prevalent form of dementia, greater than 60%, Alzheimer's disease, can have a devastating impact on a person's physical, psychological, and social development as well as their ability to work and interact with others. The diagnosis and treatment of brain tumors must be precise in order to achieve this. Due to the shortcoming of medical personnel, it is now more crucial than ever to automatically diagnose brain tumor and Alzheimer's disease in order to reduce the amount of work of medical personnel and improve the precision of medical diagnoses. For the above-mentioned diseases, detection and classification using conventional machine learning alongside deep learning, a variety of research techniques have been developed. The manual creation of features for the conventional machine learning classifiers takes a lot of time. Instead, deep learning is very reliable at extracting features, and it has been more widely applied for classification and detection purposes. As a result, in this project, an Alzheimer's detection model for three degrees of severity—very mild, mild and moderate demented, along with brain tumor detection for three types—meningioma, pituitary and glioma, and tumor segmentation model for localizing the affected region of the brain with tumor have been developed using typical MRI scans as inputs, utilizing convolutional neural networks. The accuracy of the tested Alzheimer's model was 98.37% with a weighted average percentage of 98 for precision, recall, and an F1-score, while the accuracy of the tested tumor model was 97.16% with a weighted average percentage of 97 for precision, recall, and an F1-score.

Keywords: Brain Tumor, Alzheimer's, Deep Learning, MRI, Convolutional neural networks

1. Introduction

The human brain serves as a command center and is a crucial part of the nervous system that carries out daily tasks. The body's sensory organs send stimuli or signals to the brain, which then receives them, processes them, makes the final decisions, and sends the information to the muscles. One of the most serious conditions affecting the human brain is called BTs, in which an uncontrolled growth of abnormal brain cells occurs. The two main categories of BTs are primary and secondary metastatic. Primary brain tumors (BTs) are made up of human brain cells and are typically not cancerous. In contrast, blood flow from other body parts helped secondary metastatic tumors travel to the brain. The three main categories of primary brain tumors are glioma, pituitary, and meningioma. Pituitary BTs are typically benign tumors that develop in the pituitary glands, on the underside of the brain where some of the body's most important hormones are made. The glial cells in the brain give rise to gliomas. The protective membrane surrounding one's brain and spinal cord is where meningioma tumors typically develop.

Unusual brain cells gathered together to form a tumor, resulting seizures, hearing loss, headaches that are frequent and severe, nausea, vision issues, and problems with sensation over time. Problems with memory, thinking, and behavior are symptoms of Alzheimer's disease, a type of brain disorder. The condition is one that worsens over time. Very mild, mild, and moderate dementia can be used to categorize the disorder. Both brain tumor and Alzheimer's dementia are serious illnesses; the number of people dying from brain tumors is rising; in severe cases of dementia, medical professionals typically advise immediate medical attention. The manual detection of brain diseases from MRIs takes a lot of time and is not sufficient for accurately identifying, locating, and grading them.

2. Literature Review

2.1 Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks

The system for detecting and localizing brain tumors from MRIs proposed in this paper is a two-phase, multi-model deep learning system. The main aims of this study are to accurately localize the tumor in the abnormal MRIs and to label MRIs into both normal and atypical images depending on whether a brain tumor is present or absent. For both feature extraction and classification in the first system phase, respectively, CNN and ECOCSVM approaches were used. The following system phase employed a five-layer R-CNN to localize the tumor. Using 349 MRIs taken from the RIDER Neuro MRI database, the tumor detection phase was assessed. According to empirical research, the method had an accuracy rate of 99.55 percent. Using 804 3D MRIs, a DICE score of 0.87 was obtained for the tumor localization stage utilizing the BraTS 2013 database. The achieved results demonstrated the superior performance achieved by the proposed deep learning-based approach for tumor detection as well as the performance of the entire system in terms of detection and localization methods.

2.2 Classification using deep learning neural networks for brain tumors

In this paper, the authors present an effective method for classifying brain MRIs into normal and three different types of malignant brain tumors, including glioblastoma, sarcoma, and metastatic bronchogenic carcinoma. This method incorporates the discrete wavelet transform (DWT) and deep neural networks (DNN). The new methodology's architecture is similar to that of convolutional neural networks (CNN), but it requires less hardware and processes large images (256, 256) more quickly. Additionally, compared to conventional classifiers, the DNN classifier demonstrates high accuracy. The positive outcomes obtained with the DWT can be applied to the convnet in the near future and the outcomes compared.

2.3 A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor

The use of deep learning models for the detection of brain tumors was discussed in this paper. In this essay, two distinct scenarios were evaluated. First, the features were taken from different Dens Net blocks using a previously trained DensNet201 deep neural network model. The brain tumor was then classified using the SoftMax classifier after these features were concatenated. In order to classify brain tumors, the features from various Inception components were extracted from the pre-trained Inceptionv3 model, concatenated, and then passed on to the SoftMax. Using the three-class brain tumor dataset that is openly available, both scenarios were assessed. As a result, for the classification problem of brain tumors, the ensemble method built around concatenation of dense blocks by using DensNet201 models that were previously trained outperformed the current research methods.

2.4 Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists

They present a deep learning-based automated multimodal classification method for classifying different types of brain tumors. There are five main steps in the suggested procedure. In the first step, edge-based histogram equalization and the discrete cosine transform (DCT) are used to implement the linear contrast stretching. Deep learning feature extraction is carried out in the second step. Two pre-trained convolutional neural network models, which are VGG16 and VGG19, were implemented for feature extraction by using transfer learning. The extreme learning machine (ELM) and a correntropy-based joint learning method were both used in the third step to choose the best features. The robust covariant features based on partial least squares (PLS) were combined into one matrix in the fourth step. ELM received the combined matrix to perform the final classification. The proposed approach was tested using the BraTS datasets, and for BraTs2015, 17 and 18 respectively, accuracy of 97.8%, 96.9%, and 92.5% was attained.

2.5 MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers

In their research work, they presented a method for classifying brain tumors using an ensemble of deep features from deep convolutional neural networks with machine learning classifiers that had already been trained. In the framework we propose, we obtain deep features from brain MR images using a number of previously trained deep convolutional neural networks. Several ML classifiers then evaluate the deep features that were extracted. The three most effective deep features that consistently outperform other ML classifiers are chosen, concatenated, and used as an ensemble to predict the outcome using additional ML classifiers. In their experiment, they have offered a thorough evaluation using nine different machine learning (ML) classifiers and 13 distinct previously trained deep convolutional neural networks on three separate datasets (BT-small 2c, large 2c, and large 4c) for the classification of brain tumors. Their suggested innovative feature ensemble method generates better and more robust efficiency, especially for large datasets, by overcoming the limitations of a single CNN model. These findings showed that the brain tumor classification method we proposed, which combines a set of deep features with machine learning classifiers, is effective. Even though our suggested approach performs well, more research must be done to shrink the model's size so that it can be implemented on an actual-time medical evaluation system using knowledge distillation techniques.

2.6 A decision support system for multimodal brain tumor classification using deep learning

In their study, a sophisticated deep-learning automated system for classifying brain tumors into four categories—T1W, T1CE, T2W, and Flair—is presented. This system might be helpful for radiologists seeking a second opinion because brain MRI scans are a more useful imaging tool for analyzing brain tumors. Due to the high similarity between tumor stages, multiclass classification of brain tumors is a challenging and difficult task. Additionally, current systems are effective at balancing datasets, which might not be a good method because a number of images are overlooked during the learning process. This method's main advantage is its use of MGA and Entropy-Kurtosis-based techniques to choose the best features. These suggested methods shorten the classification process while enhancing the system's accuracy. The combination of the best features to increase the proposed accuracy was their work's second strength. Their research process demonstrates that the suggested approach significantly enhances the datasets chosen. Future experiments using more recent deep learning techniques on the BRATS2019 datasets will be conducted. Their work's primary drawback was the elimination of some crucial components that affected the system's accuracy. The fusion process also lengthens the computation time.

2.7 A Hybrid Deep Learning-Based Approach for Brain Tumor Classification

The goal of this study was to categorize BTs using new hybrid models and various convolution neural networks. The proposed DeepTumorNet framework was built on top of the GoogleNet architecture. GoogleNet's final five layers were removed, and 15 new, deeply nested layers have been included in their place. Without altering the fundamental design of the convolution neural network, the ReLU activation function was converted into what is known as leaky ReLu activation function. After the modifications, there were 154 layers overall as opposed to 144. The proposed hybrid model achieved a classification accuracy of 99.67%, which was the highest ever. Furthermore, they applied nine deep pre-trained CNN models to the CE-MRI dataset using a transfer learning approach to identify the BT types, and they compared the outcomes with the proposed hybrid model. The experimental results demonstrated that the proposed hybrid model was more effective at differentiating brain tumours. Additionally, the proposed approach computed more precise and selective specifics along with exact features for the classification of tumour, yielding high accuracy, when compared to other state-of-the-art methods.

2.8 An MRI-based deep learning approach for accurate detection of Alzheimer's disease

This research led to the creation of a DNN-based pipeline that can accurately detect multiple classes of Alzheimer's disease in brain MR images. The proposed pipeline showed 99.68% accuracy, 100% sensitivity, 100% specificity, and 100% ROC, respectively. 6400 brain MRIs were used as the data set for validation and testing. By comparing their framework's performance to that of well-known CNNs, we were able to confirm higher multi-class classification while also confirming the robustness of the method using ROC analysis. Their method's higher accuracy suggests its use for determining different stages of Alzheimer's disease for a variety of age groups by carefully choosing the network architecture. In their upcoming work, they will combine various datasets using progressed data mining algorithms in order to improve the performance and efficacy of AD prediction at earlier stages using various datasets and stages.

2.9 An MRI Scans-Based Alzheimer's Disease Detection via Convolutional Neural Network and Transfer Learning

One of the key pillars of the smart city vision is smart health, which calls for cutting-edge technology to enhance the current healthcare infrastructure. In this study, it is hypothesized that automatic diagnosis of Alzheimer's disease by employing a model that uses machine learning could decrease the time commitment of medical personnel and improve the precision of medical diagnoses. The GAN-CNN-TL algorithm that is proposed in this paper offers the benefits of increased data generation, decreased biased detection model, automatic extraction of features, and improved hyperparameter tuning. The effectiveness of the proposed method, which improves the accuracy of the detection model by 2.85–3.88%, 2.43–2.66%, and 1.8–40.1% in the surgical removal examination of GAN as well as TL, as well as the comparison with existing works, was demonstrated by performance assessment and evaluation using three benchmark OASIS-series datasets.

2.10 VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection on MRI Images

In this paper, different traditional and hybrid ML models were built and analyzed in detail to classify the brain tumor images without any human intervention. Along with these, 16 different transfer learning models were also analyzed to identify the best transfer learning model to classify brain tumors based on neural networks. Finally, using different state-of-the-art technologies, a stacked classifier was proposed which outperforms all the other developed models. The proposed VGG-SCNet's (VGG Stacked Classifier Network) precision, recall, and f1 scores were found to be 99.2%, 99.1%, and 99.2% respectively.

3. Conclusion

This project's main goal is to identify and categorize brain tumor and Alzheimer's diseases. Additionally, it divides the area of the brain where the tumor is located. To carry out the project, we combined CNN and Deep Learning methods. On the testing data of the Alzheimer's dataset, we have a 98.37% accuracy. Similarly, the testing data from the Brain tumor dataset had an accuracy of 97.48%. The website assists neurologists in more accurately identifying brain tumors and Alzheimer's disease early on, allowing patients to receive treatment before the condition worsens.

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