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Identification and Categorization of Brain Tumors

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Abstract

Brain tumors are a serious and aggressive disease that can lead to a reduced life expectancy. Strategic and well-thought-out treatment planning significantly contributes to improving a patient's overall quality of life. Many different imaging techniques, such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) and also ultrasound are used to evaluate tumors in different parts of the body, with a focus on using MRI images for brain tumors. It is difficult and time consuming to scan the data generated by techniques such a MRI which is huge. To overcome this limitation, automated classification methods are necessary to improve diagnosis and prevent deaths. The task of automatically detecting brain tumors is particularly challenging due to the large spatial and structural variability of the surrounding tissue. This study suggests the utilization of Convolutional Neural Networks (CNN) for the automated detection of brain tumors. The CNN architecture is designed using small kernels and neurons with small weights. The experimental findings demonstrate that the suggested approach attained an impressive accuracy rate of 97.5% while maintaining a lower level of complexity in comparison to leading-edge methodologies.

Keywords: NeuralNetworks, MRI, Brain Image, convolutional neural networks, support vector machines

INTRODUCTION

A brain tumor is a medical condition in which cells in the brain grow uncontrollably, forming a mass called a tumor. Brain tumors can be divided into two primary groups: benign and malignant. Non-malignant tumors are not cancerous and do not spread to other areas of the brain. They may cause complications due to their location, and may require surgery or radiation therapy [1]. Malignant tumors, also known as brain cancer, are cancerous and can spread to other parts of the body, leading to life-threatening complications if left untreated. They require aggressive treatment. Brain cancer can be categorized into two types: primary brain cancer, which originates within the brain itself, and secondary or metastatic brain cancer, which spreads to the brain from other parts of the body.

Magnetic resonance imaging (MRI) is a prevalent method employed to identify and evaluate brain tumors. MRI scans offer detailed insights into the brain's structure and can identify abnormalities in brain tissue. Automated approaches like neural networks (NN) and support vector machines (SVM) are employed to identify and categorize brain tumors using MRI images. Deep learning models have recently gained prominence in the field of medical image analysis due to their ability to capture intricate relationships effectively, eliminating the need for extensive nodes as seen in traditional architectures like K-Nearest Neighbor

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(KNN) and SVM. Consequently, deep learning has emerged as an advanced technology in various domains of health informatics, including medical image analysis, medical informatics, and bioinformatics.

RELATED WORKS

In the field of brain tumor detection and classification, various techniques have been proposed and implemented. These techniques include Fuzzy C-Means (FCM) segmentation, wavelet feature extraction, and deep neural networks (DNNs) for high accuracy classification. Nonetheless, these approaches frequently exhibit significant computational intricacy and limited effectiveness

Another approach that has been proposed is a bio-physico mechanical tumor growth modeling to analyze the step-by-step growth of tumors in patients. This technique combines discrete and continuous methods for tumor growth modeling, but it can have a high computation time.

Enhanced AdaBoost classification strategies and the extraction of multi-fractal features have also found application in detecting and segmenting brain tumors. These techniques possess elevated intricacy and are utilized to capture the texture characteristics of brain tumor tissue [2].

Local independent projection-based classification (LIPC) and seeded tumor segmentation methods have also been proposed, but they have low accuracy and may require explicit regularization.

A novel multimodal brain tumor segmentation scheme has been proposed that combines different segmentation algorithms for improved performance, but it also comes with a high complexity.

We've presented an outline of brain tumor segmentation techniques, which include approaches like region-based segmentation, threshold-based segmentation, fuzzy C-Means segmentation, atlas-based segmentation, MRF segmentation, deformable models, and geometric deformable models. The accuracy, robustness, and validity of these methods have been analyzed.

The process of diagnosing brain tumors has involved employing hybrid feature selection alongside ensemble classification. Utilizing approaches like GANNIGMAC, decision trees, and Bagging C-based wrapper technique, decision rules are derived and streamlined through a hybrid feature selection approach [3].

Another strategy involves the application of fuzzy-based control theory to segment and classify brain tumors. The Fuzzy Inference System (FIS), a specific method, is employed for brain segmentation, and supervised classification is utilized to generate a membership function for a fuzzy controller.

Adaptive histogram equalization and Gabor feature extraction have also been used to improve the contrast of images and filter abnormal cells in the brain, followed by fuzzy K-Nearest Neighbor (KNN) classification.

Finally, a novel automatic brain tumor classification method using convolutional neural networks (CNNs) has been proposed, with a deeper architecture design using small kernels and neurons with small weights. The experimental results show that the CNNs achieve a high accuracy rate of 97.5% with low complexity compared to other state-of-the-art methods.

PROPOSED SYSTEM

The utilization of neural network architectures and setups is widespread, particularly in tasks such as vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification techniques. These neural network models aim to simulate the operations of the human brain. Neural networks can be categorized into three primary types according to their connectivity: Feedback, feedforward, and iterative networks.

Feedforward neural networks are further divided into single-layer and multilayer networks. Single-layer networks have no hidden layers, only input and output layers. However, multi-layer networks comprise an input layer, a concealed layer, and an output layer. On the other hand, a recurrent network operates as a closed-loop feedback system [4].

A convolutional neural network (CNN) is a specialized type of feedforward neural network designed explicitly for image processing purposes. Unlike regular neural networks, CNNs can process scalable images. That is, it can accept a 3D input volume and produce a 3D output volume. In general, CNN architectures include input layers, convolutional layers, Rectified Linear Unit (ReLU) layers, pooling layers, and fully connected layers [5].

A block diagram of CNN-based brain tumor classification is shown in Figure 1. The CNN-based classification of brain tumors is divided into two phases: training and testing. The training stage involves preprocessing, extracting features, and applying classification using a loss function to build a predictive model. During the testing phase, predictive models are used to classify new images into different categories such as tumor brain images and non-tumor brain images.

The CNN model being suggested utilizes pre-trained models that rely on the ImageNet dataset to perform classification. Training all layers from scratch can be time-consuming and perform poorly, so the proposed method only trains the last layer. A loss function is computed using the gradient descent algorithm and is used to measure the quality of a given set of parameters and improve the accuracy of the model. The gradient of the loss function is repeatedly evaluated to improve the accuracy of classification [6].

- An important benefit of CNNs lies in their capacity to autonomously and flexibly learn spatial hierarchies of features from input images. This is done by stacking multiple Successive layers of convolutional and pooling operations gradually extract increasingly complex features from the input image.

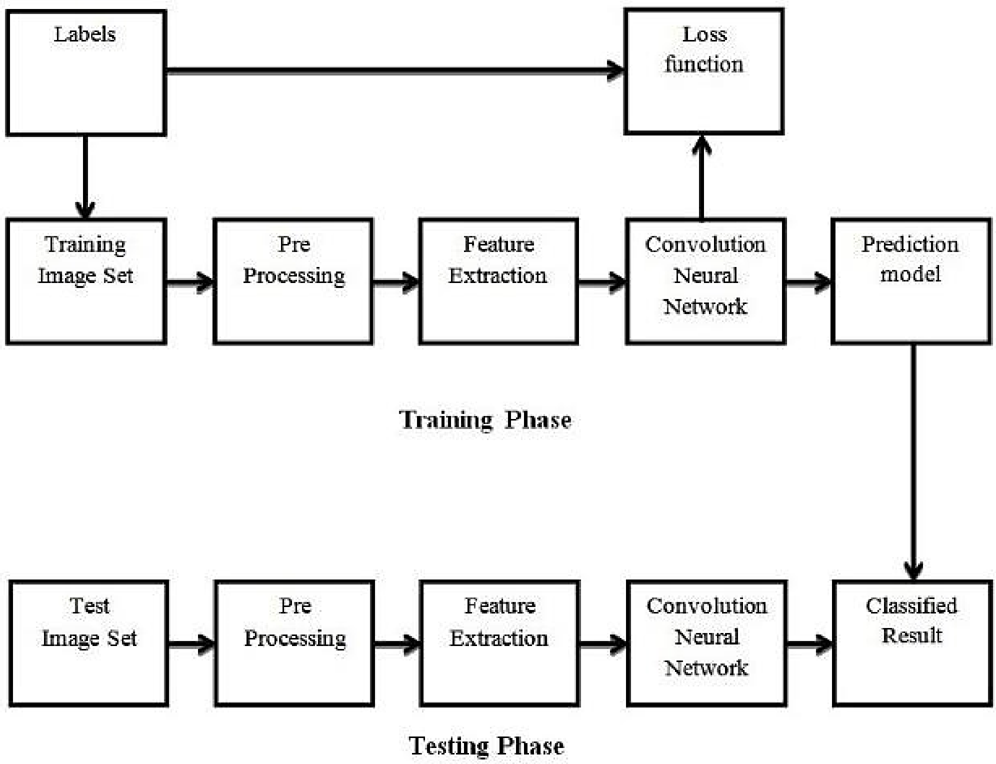

Figure 1. Testing phases.

- Another advantage of CNNs is their ability to reduce the number of parameters that need to be trained, which makes them more efficient and less prone to overfitting than traditional neural networks. This is accomplished by employing convolutional and pooling layers with shared weights, ultimately reducing the spatial resolution of the input image. In recent years, various architectures such as VGGNet, ResNet, Inception, and DenseNet have been proposed to improve the performance of CNNs on a wide range of image classification tasks. These architectures are designed to improve the representational capacity of the network, reduce overfitting, and improve the gradient flow during training.
- In addition to image classification, CNNs are applied in a range of other computer vision tasks such as object detection, semantic segmentation, and image generation. In the medical field, CNNs have been widely used for image analysis, such as for the segmentation and classification of brain tumors, lung tumors, and breast tumors. By using pre-trained models and fine-tuning the model with a small dataset of medical images, it can improve the performance and reduce the computation time.
- In brain tumor classification, CNNs have been shown to achieve high accuracy rates, even when compared as seen in Figure 2.

Algorithm for CNN based Classification

1. Utilize the convolutional filter within the initial layer.
2. Subsample the convolution filter to make it less sensitive.
3. he activation layer regulates the signal flow from one layer to another [7].
4. Shorten the training period by employing rectified linear units (RELUs), which connect every neuron in the layer below with the neurons in the layer above.
5. To provide the neural network with feedback during training, a loss layer is included at the end [8].

RESULTS AND DISCUSSION

Tumor and non-tumor MRI images were gathered for our dataset from various web sources.

The brain tumour image segmentation benchmark (BRATS) 2015 testing dataset and Radiopaedia both feature real-world patient cases and tumour images, respectively.

In this research, convolutional neural networks are employed to perform efficient automated detection of brain tumors [9].

Python is used to carry out the simulation.

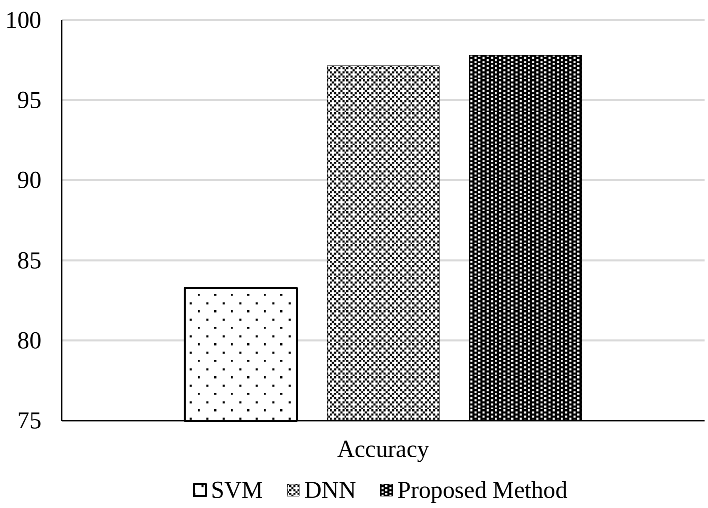

Figure 2. Model accuracy.

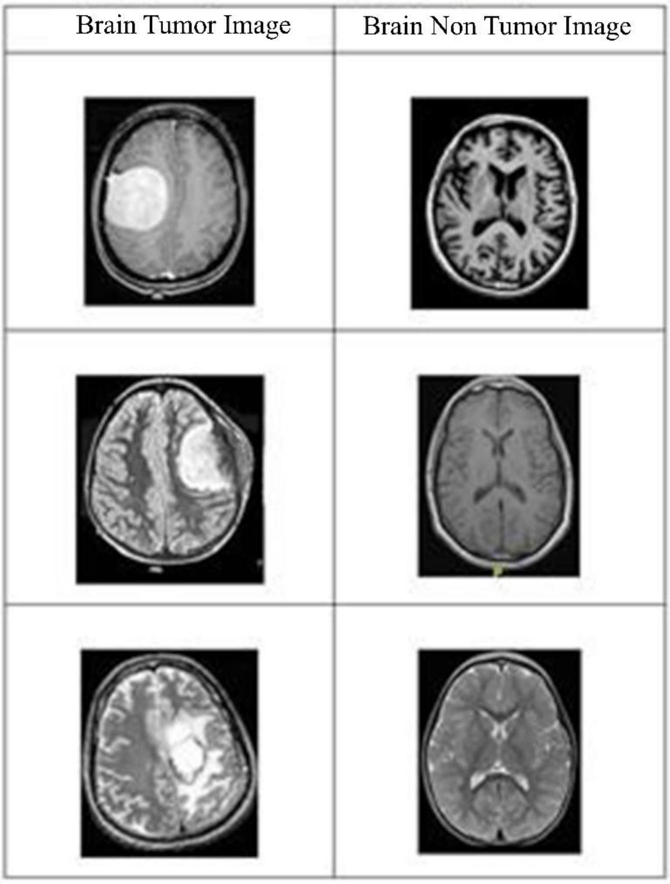

Figure 3. Classification result.

The accuracy is calculated and evaluated against all other cutting-edge techniques.

According to evaluations of training accuracy, validation accuracy, and validation loss, SVM-based tumor and non-tumor identification exhibits prolonged computation time and diminished accuracy as seen in Figure 3.

1. The proposed brain tumor classification method utilizing a CNN is represented in a block diagram
2. Accuracy of brain tumor classification
3. CNN based classified results

Since the feature value is directly obtained from the CNN, the classification method using the proposed CNN does not require a separate feature extraction. The brain imaging classification for tumours and non-tumors is shown in the above figure. Consequently, there is a notable increase in accuracy, while computational complexity and time requirements remain minimal. The results of the accuracy of brain tumour classification are also displayed. Based on probability score values, the classification findings separate tumour brain from non-tumor brain, with normal brain images having the lowest probability score and tumour brain having the greatest when compared to the other two categories [10].

CONCLUSION

The goal of this project is to create an effective system for automatically classifying brain tumours that achieves high performance and accuracy with little complexity. Using Fuzzy C Means (FCM) segmentation, texture and form features are extracted, and the data is then classified using Support

Vector Machines (SVMs) or Deep Neural Networks, according to conventional techniques for diagnosing brain tumours (DNNs). These techniques are simple, but they take a long time to compute and are inaccurate.

To address these constraints, this study suggests the utilization of a classification system based on convolutional neural networks (CNNs). CNNs are a form of deep learning methodology that employs a series of feedforward layers. The implementation is in Python and uses the ImageNet database for classification. The proposed system requires training only the last layer and achieves high accuracy while reducing computational time. From the CNN, features including raw pixel values, depth, width, and height are extracted. Accuracy is further improved by using a gradient descent based loss function. The training accuracy reaches 97.5%, with a notable elevation in validation accuracy and a concurrent reduction in validation loss.

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