STM JOURNALS

International Journal of
Cheminformatics

Volume 1, Issue 1, 2023
January—June
DOI (Journal): 10.37591/IJCI

https://journals.stmjournals.com/ijci/

Review IJCI

Classification and Detection of Brain Tumor using Convolutional Neural Network

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Abstract

Tumors are masses created when brain cells multiply uncontrollably. A brain tumor is the medical term for this condition. Brain tumors are a serious and aggressive disease that can lead to a reduced life expectancy. Developing a treatment plan is essential to raising a patient's standard of living. Tumors in different regions of the body are evaluated using a variety of imaging techniques, with MRI pictures being utilized mostly for brain tumors. These techniques include Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and ultrasound. Scanners have a hard time processing the massive amounts of data produced by MRI procedures. To overcome this limitation, automated classification methods are necessary to improve diagnosis and prevent deaths. Because the surrounding tissue is so variable in both space and structure, automatically recognizing brain tumors is a particularly difficult undertaking. The traditional techniques for diagnosing DNNs entail segmenting the data and extracting texture and form features using Fuzzy C Means (FCM). The data is subsequently classified using Deep Neural Networks or Support Vector Machines (SVMs). Many applications, such as vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification algorithms, make extensive use of neural network designs and implementations. These techniques are simple, but they calculate slowly and with impreciseness. The use of Convolutional Neural Networks (CNN) for automatic brain tumor detection is suggested in this paper. Small neurons and kernels with small weights are used in the construction of the CNN architecture. In comparison to other cutting-edge techniques, the testing results demonstrate that the suggested method attained a high accuracy of 97.5% with minimal complexity.

Keywords: Neural networks, MRI, brain tumor, convolutional neural network, brain imaging

INTRODUCTION

A tumor is a growth that develops when brain cells multiply uncontrollably. This disease is known as a brain tumor. Benign and malignant are the two basic classifications for brain tumors. Benign tumors don't cause cancer. Because of their placement, they could cause issues and necessitate radiation therapy or surgery. If left untreated, malignant tumors, commonly referred to as brain cancer, can spread to other parts of the body and cause potentially fatal problems. They need to be treated aggressively. Furthermore, brain cancer can be classified into two types: primary brain cancer, which originates in the brain, and secondary or metastatic brain cancer, which spreads to the brain from another part of the body.

Magnetic resonance imaging (MRI) is a common tool used to diagnose and monitor brain tumors. It can provide detailed information about the anatomy

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Received Date: March 11, 2024
Accepted Date: April 02, 2024
Published Date: April 14, 2024

Citation: Jinal Pravin Gala, Hemant Mahendra Gupta. Classification and Detection of Brain Tumor using Convolutional Neural Network. International Journal of Cheminformatics. 2023; 1(1): 8–13p.

of the brain and identify abnormalities in brain tissue. Automated techniques like support vector machines (SVM) and neural networks (NN) are used to identify and categorize brain tumors based on MRI images [6]. Because deep learning models can effectively express complicated relationships without requiring a huge number of nodes, as in classic designs like K-Nearest Neighbor (KNN) and SVM, they have recently acquired appeal in the field of medical picture analysis. It's becoming more and more well-liked [3]. It has thus emerged as a cutting-edge technique in a number of health informatics domains, including bioinformatics, medical informatics, and medical image analysis [1].

RELATED WORKS

Numerous methods have been put forth and put into practice in the field of brain tumor detection and categorization. These methods include deep neural networks (DNNs) for high accuracy classification, wavelet feature extraction, and fuzzy C-Means (FCM) segmentation. Nevertheless, these techniques frequently have poor performance and a large computational cost.

To examine the progressive development of tumors in patients, a bio-physico-mechanical tumor growth modeling method has also been suggested. This technique combines discrete and continuous methods for tumor growth modeling, but it can have a high computation time.

Brain tumor segmentation and identification have also been accomplished through the use of enhanced AdaBoost classification algorithms and multi-fractal feature extraction [5]. These incredibly complex processes are used to obtain the texture of brain tumor tissue. 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 [4].

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.

A study of techniques for segmenting brain tumors has been provided, encompassing deformable models, geometric deformable models, fuzzy C-Means, region-based, and MRF segmentation [9]. These techniques' validity, accuracy, and robustness have all been examined [7].

To diagnose brain tumors, hybrid feature selection and ensemble classification have been used. To get decision rules and make them simpler utilizing a hybrid feature selection method, decision tree, and Bagging C based wrapper approach has been employed.

Segmenting and classifying brain tumors have also been done using fuzzy based control theory. A sophisticated method called the Fuzzy Inference System (FIS) is utilized to partition the brain and generate a fuzzy controller's membership function using supervised categorization [10].

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.

Ultimately, a deeper architecture design employing small kernels and neurons with small weights has been presented for a unique automatic brain tumor classification approach using convolutional neural networks (CNNs).

In comparison to other cutting-edge techniques, the testing results demonstrate that CNNs attain a high accuracy rate of 97.5% with minimal complexity [1, 2]

PROPOSED SYSTEM

Many applications, such as vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification algorithms, make extensive use of neural network designs and implementations. These designs and implementations are used to represent the human brain. Based on

ISSN: 2230-9845 (Online), ISSN: 2321-516X (Print)

connection, neural networks can be categorized into three primary types: feedforward, iterative, and feedback networks.

There are two types of feedforward neural networks: single-layer networks and multilayer networks. Multilayer networks have input, hidden, and output layers. A recurrent network is a closed-loop feedback network.

One kind of feedforward neural network created especially for image processing is the convolutional neural network (CNN). CNNs are able to process scaled images, in contrast to ordinary neural networks. Put otherwise, it is capable of producing and receiving 3D volumes. CNN topologies typically include input layers, convolutional layers, pooling layers, Rectified Linear Unit (ReLU) layers, and fully connected layers. Figure 1 displays a block schematic of CNN-based brain tumor classification. There are two stages to the CNN-based brain tumor categorization process: training and testing. Preprocessing, feature extraction, and classification using a loss function are all part of the training step, which builds a predictive model. Predictive models are employed in the testing phase to categorize fresh images into distinct groups, such as brain images of tumors and brain images without tumors.

For classification, the suggested CNN makes use of pre-trained models built using the ImageNet dataset. Training all layers from scratch can be time-consuming and perform poorly, so the proposed method only trains the last layer. The gradient descent process is used to generate a loss function, which is then used to assess the quality of a given set of parameters and increase the model's accuracy. Continually assessing the loss function's gradient enhances classification accuracy.

- CNNs' capacity to automatically and adaptively learn the spatial hierarchies of information from input images is one of its main advantages. Multiple layers of convolutional and pooling processes are stacked to achieve this, eventually extracting higher level characteristics from the input image [8].
- 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. Convolutional and pooling layers, which have the same weights and lower the input image's spatial resolution, are used to accomplish this.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.
- CNNs have been used for computer vision applications such as object identification, semantic segmentation, and image synthesis in addition to image classification.
- CNNs have been widely used in the medical industry for image analysis, including the segmentation and classification of breast, lung, and brain cancers. Pre-trained models can be used to increase performance and decrease computation time by fine-tuning the model with a limited sample of medical images.
- In brain tumor classification, CNNs have been shown to achieve high accuracy rates, even when compared.

Algorithm for CNN based Classification

1. The first layer needs to have a convolution filter applied to it.
2. Reduce the sensitivity of the convolution filter by subsampling it.
3. The signal flow between layers is controlled by the activation layer.
4. Repaired linear units (RELUs), which link each neuron in the layer below with all the neurons in the layer above, can be used to reduce the training time.
5. An end loss layer is added to the neural network to give it feedback while it is being trained [1] [Figure 1] [3].

RESULTS AND DISCUSSION

For our dataset, MRI pictures of tumors and non-tumors were collected from multiple websites.

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

In this work, effective automatic brain tumor detection is achieved by the application of convolution neural networks. The simulation is run using Python. The accuracy is computed and compared with every other state-of-the-art method. Calculations of training accuracy, validation accuracy, and validation loss show that in SVM-based tumor and non-tumor identification, the efficiency computation time is high, and the accuracy is low [1] [Figure 2].

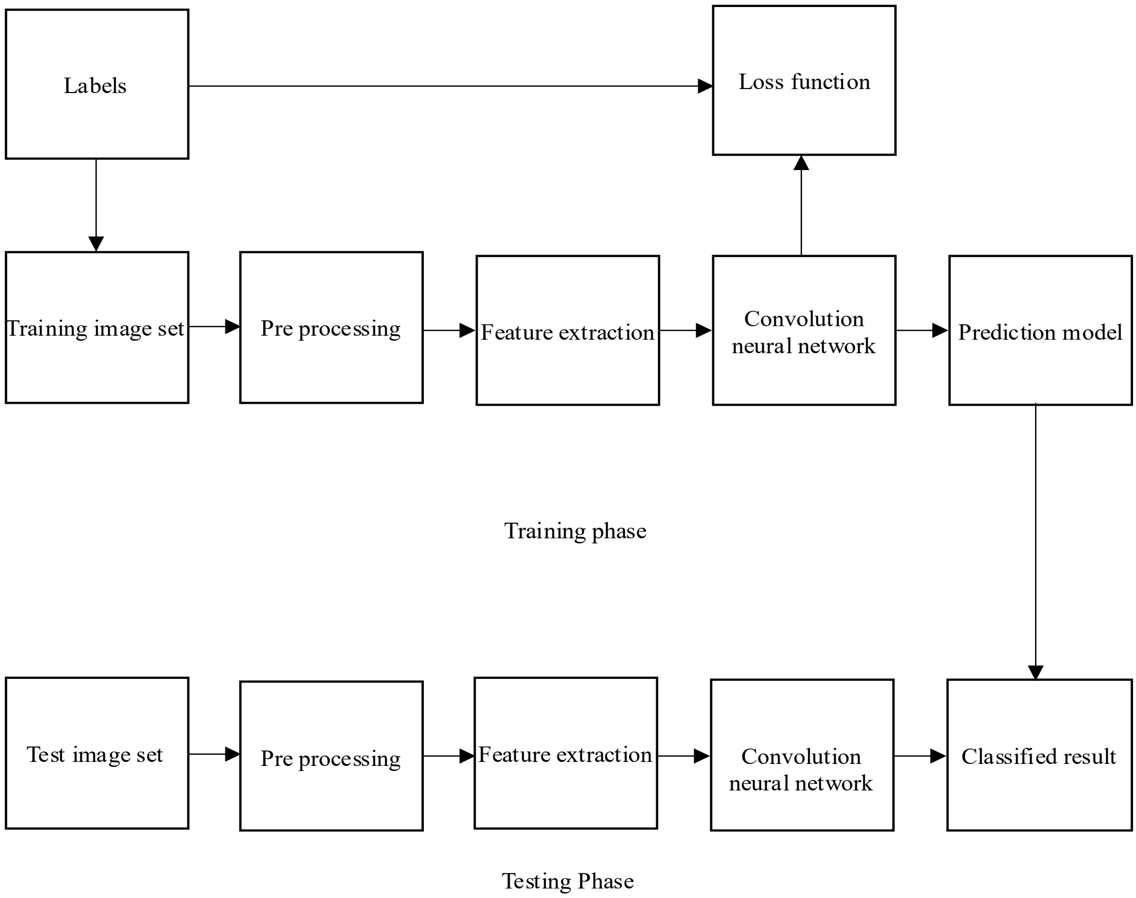

Figure 1. The suggested CNN-based brain tumor categorization approach is shown in a block diagram.

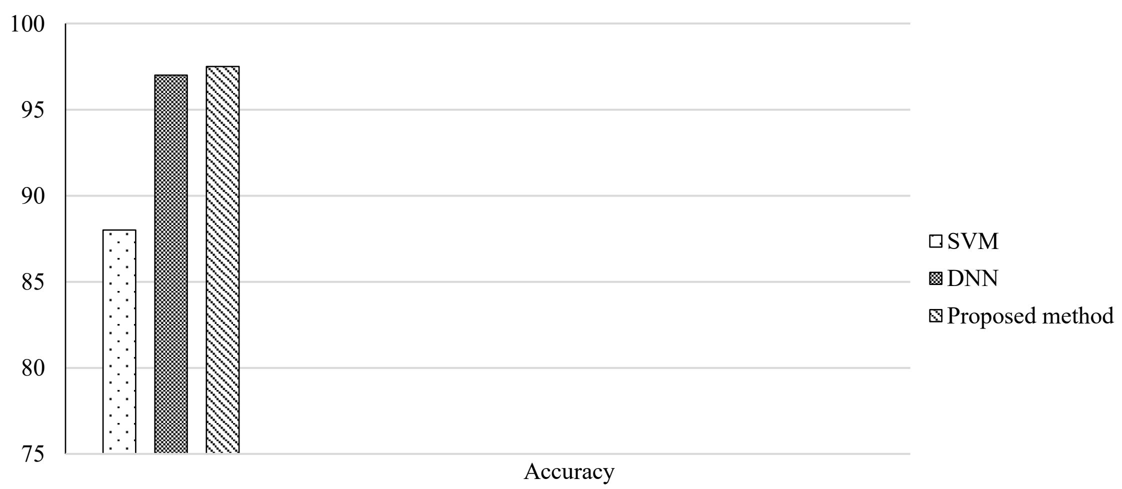

Figure 2. Model Accuracy: *Precision in brain tumor categorization.*

Brain tumor image	Brain non tumor image
	
	
	

Figure 3. Classification result *sorted by CNN.*

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 tumors and non-tumors is shown in the above figure. As a result, accuracy is high and computation complexity and time are minimal. Also shown are the findings of the classification accuracy for brain tumors. The classification results distinguish tumor brain from non-tumor brain based on probability score values; in comparison to the other two groups, normal brain images have the lowest probability score and tumor brain images have the highest [1] [Figure 3].

CONCLUSION

The objective of this project is to design a low-complexity, high-performance, automatically-classified brain tumor classification system.Conventional methods for diagnosing brain tumours (DNNs) involve segmenting the data using Fuzzy C Means (FCM) to extract texture and form features. Support Vector Machines (SVMs) or Deep Neural Networks are then used to classify the data. These methods are straightforward, but they are imprecise and calculated slowly.

This work suggests employing a convolutional neural network (CNN)-based classification system in order to get around these restrictions. CNN is a deep learning method that uses feedforward layers. The computation is done using the ImageNet database in a Python implementation.

The suggested method reduces calculation time and delivers excellent accuracy by only requiring training the final layer. The CNN is used to extract features such as depth, breadth, and height as well as raw pixel data. Using a loss function based on gradient descent further increases accuracy. There is a 97.5% training accuracy, a high validation accuracy, and a low validation loss.

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