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Automated classification of brain tumors based on the convolutional neural network

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Abstract. The treatment of brain tumors, utilizing conventional methods such as surgery, radiotherapy, and chemotherapy, is limited in terms of accuracy and effectiveness. Furthermore, there exists a possibility of missing the diagnosis for small lesions and certain benign tumors with comparable density to normal tissue. To improve the precision and efficiency of brain tumor diagnosis, recent developments in artificial intelligence have been explored, including the use of Convolutional Neural Networks (CNNs). This research investigates the potential of a four-class CNN-based deep learning algorithm for the diagnosis of brain tumors. A dataset of MRI images, including various forms of brain tumors, underwent preprocessing and cleansing, and was subsequently classified into four categories. The CNN model trained to identify and diagnose MRI images achieved an 85.4% accuracy on the validation set. This study underscores the potential of CNNs to enhance the detection and precision of brain tumors, in addition to improving the consistency and dependability of diagnosis, thereby providing new leads for the discovery of novel therapies and medications. However, the study recognizes that limitations and areas of improvement exist in terms of dataset size, model architecture, and evaluation metrics.

Keywords: brain tumors prediction, Convolutional Neural Network (CNN), MRI images.

1. Introduction

Brain malignancies and intracranial tumors are new organisms that are developing in the cerebral cavity. They may originate directly from an organ, such as the brain, meninges, or nerves, or they may spread from other bodily parts into the brain by metastasis. The majority of these tumors can result in localized symptoms such headaches and intracranial pressure [1]. Brain tumors vary greatly in size, with some being detected early due to noticeable symptoms, while others grow undetected until they become quite large. Brain tumors affect roughly 1.9 to 5.4 people per 100,000 people annually, accounting for 1% to 3% of all body tumor types. In order to run simulations and forecast results, recent developments in artificial intelligence (AI) offer the chance to integrate and synthesis ever-increasing volumes of multidimensional data. This will improve shared decision-making for patients and physicians.

As the three pillars of tumor treatment, surgery, radiotherapy, and chemotherapy play an important role. However, when encountering tumors located in hollow organs, particularly in the gastrointestinal system, the diagnosis is often challenging due to the thin intestinal wall and the presence of gas, digestive juice, and food residues that may impede accurate imaging. In addition, for small lesions and some benign tumors with the same density as normal tissue, due to the partial volume effect, it is easy to miss the diagnosis. In summary, manual errors in early diagnosis methods may occur. The most recent artificial intelligence technology must be used to improve tumor diagnosis and prediction in order to increase the recognition and accuracy of brain tumors [2].

Convolutional Neural Network (CNN) technology is among the most cutting-edge forms of artificial intelligence and has a significant impact on a variety of industries, including image recognition, speech recognition, natural language processing, and others [3-7]. CNN can automatically learn abstract and high-level features in brain tumor images without manual feature selection and extraction. This can improve diagnostic accuracy and reduce the need for manual intervention. Additionally, CNNs were able to identify and classify images of brain tumors with a high degree of accuracy. Compared with traditional image processing methods, CNN can better distinguish different types of tumors and can detect tiny abnormal areas, thus improving the accuracy of diagnosis. More importantly, CNN is highly reproducible and can produce similar results across different experimental conditions and different datasets. This ensures the reliability and consistency of diagnosis, thereby improving the reliability of clinical application, helping medical researchers better understand the morphology and characteristics of brain tumors, thereby providing more clues and ideas for discovering new treatments and drugs. Therefore, this paper presents a CNN-based approach for automated classification and prediction of brain tumors.

This study aims to investigate the use of a deep learning algorithm built on a four-class convolutional neural network for brain tumor identification. This study used a dataset of MRI images containing different types of brain tumors for experiments. The dataset is separated into four categories after preprocessing and cleaning. Then, a trained four-class model was utilized to classify and diagnose MRI images. Finally, this study evaluated and validated the models, and analyzed and compared the diagnostic results.

2. Method

In this project, a series of brain tumor's MRI picture dataset provided by a dataset on Kaggle was obtained [8]. The dataset was pre-processed and organized into separate Training and Testing folders, with each folder containing four subfolders that correspond to different tumor classes. These folders have MRIs of respective tumor classes, which respectively concludes 2, 870 and 394 images. The images were grayscale and measured 512×512 pixels in size. Figure 1 depicts an exemplar image in its original form.

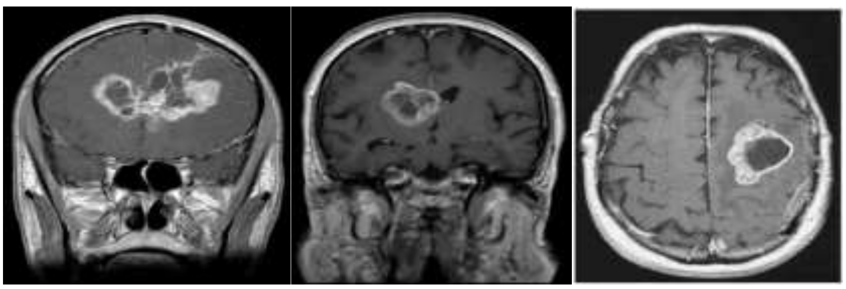

Figure1. The example images of brain tumor.

The data preprocessing step comprises three essential components. First, train_datagen object is created with the following parameter: rescale=1./255. This normalizes the pixel values of the images by dividing each pixel value by 255. Second, the test_datagen object is also created with the same parameter to ensure consistency in data preprocessing between the training and validation datasets. By applying multiple picture transformations, the ImageDataGenerator function also does data augmentation on the training dataset. By doing so, overfitting is decreased and the training dataset's diversity is increased. Third, the set of the data was resized into 256×256 and the batch size is 32, the class mode is categorical.

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Several layers make up the CNN model, each of which is intended to extract and learn pertinent characteristics from the input images. A convolutional layer is created by combining several filters, and it pulls features from the input image. Each filter reacts to a certain characteristic or pattern in the image. The output of the convolutional layer is a set of feature maps indicating the presence of distinct features in the input image. Pooling Layer reduces the spatial dimensions of the feature maps through downsampling. The most common sort of pooling layer is the MaxPooling layer, which selects the greatest value within a window of pixels and ignores the remainder. The activation layer gives the model additional non-linearity by applying a non-linear activation function to the output of the layer before it. ReLU and sigmoid are two often used activation functions [9]. The fully connected layer is similar to the layers in a traditional neural network and is used to classify the entrance image according to the characteristics learned. One or more fully connected layers receive the flattened and inserted exit of the convolutional and pooling layers. The probability distribution for the various classes is generated via a softmax activation feature in the final fully connected layer. In order to prevent overflow, drop-out layers randomly remove a portion of the neurons from the preceding layer during training.

Four Conv2D layers with progressively larger filter widths of 32, 64, 128 and 256 make up his pattern architecture. The spatial dimensions of the characteristic maps are decreased by adding a MaxPooling2D layer with a pool size of (2, 2) after each Conv2D layer. The Flatten layer reduces the characteristic maps to a one-dimensional vector, which is then transferred to two thick layers with 128 units each that are entirely interconnected. Meningioma, glioma, pituitary tumor, and no tumor are the four tumor classifications for which probability distributions are produced by the first dense layer using ReLU activation and the second dense layer using a softmax activation function [10]. After the first Dense layer, the Dropout layer with a rate of 0.5 is introduced to prevent overflowing by randomly removing 50% of the neurons during training.

In this code, the GPU is commented out, which means that the model is trained on the GPU. Training a deep learning model on a GPU can be several times faster than training on a CPU, especially for large datasets and complex models. The optimizer used in this code is Adam. The CNN model's loss function, which calculates the difference between the predicted and actual probability distributions, and loss, which calculates the proportion of correctly categorized images, both use categorical cross-entropy.

3. Results and discussion

Using a collection of brain MRI pictures divided into four classes—meningioma, glioma, pituitary tumor, and no tumor—the CNN model was trained. The model's accuracy on the validation set, which is displayed in Table 1, was 85.4% after being trained for 10 epochs with a batch size of 32.

Table 1. The performance processed on the brain tumor dataset.

Model	Scale
Training Loss	0.4726
Training Accuracy	0.7321
Testing Loss	0.6231
Testing Accuracy	0.8543

The presented model has achieved a noteworthy level of accuracy on the validation set, indicating its efficacy in accurately classifying brain MRI images into the four distinct tumor categories. However, there are some limitations and potential areas for improvement. Firstly, the dataset used in this code only contains a limited number of images (3064 training images and 535 validation images). A larger dataset with more diverse images could potentially improve the model's performance.

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Secondly, the model architecture employed in this code is comparatively simple, involving only four convolutional layers and one fully connected layer. More complex architectures, such as those using residual connections or attention mechanisms, could potentially improve the model's performance. Lastly, it is important to note that the accuracy metric alone may not be sufficient to evaluate the model's performance, especially in medical image analysis tasks where false negatives and false positives can have serious consequences. Other metrics such as sensitivity, specificity, and positive predictive value should also be taken into account.

4. Conclusion

In conclusion, this study explored the application of a four-class convolutional neural network in the diagnosis of brain tumors using MRI images. The dataset was pre-processed and organized into separate training and testing folders, with each folder containing four subfolders that correspond to different tumor classes. The trained model correctly classified the four different tumor types in the validation set with an accuracy of 85.4%, demonstrating its effectiveness in identifying brain MRI images. However, there are potential areas for improvement, such as using a larger and more diverse dataset and employing more complex model architectures. Additionally, it is important to consider metrics beyond accuracy, such as sensitivity and specificity, in evaluating the model's performance in medical image analysis tasks. Overall, the use of CNN-based approaches in the diagnosis and prediction of brain tumors has great potential to improve diagnostic accuracy, reduce the need for manual intervention, and provide more clues for discovering new treatments and drugs.

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