Brain Tumor Detection Using Convolutional Neural Network in Mobile Devices

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***Abstract* - Aiming at solving the problem of low accuracy in traditional brain tumor detection and increasing the accessibility of detection techniques to people. The automatic brain tumor classification is an incredibly challenging task in large spatial and structural variability of surrounding region of brain tumor. In this work, automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification. The deeper architecture design is performed by using small kernels. The weight of the neuron is given as small. Experimental results show that the CNN archives rate of 88.7% accuracy with low complexity and compared with the all- other state of arts methods. And about integrating models with mobile devices in order increase usability and to provide a better experience through offline support for detection.**

INTRODUCTION

Brain tumors can be classified into two types: benign (noncancerous) and malignant (cancerous). The malignant tumors can quickly spread to other tissues in the brain and lead to worsening the patient's condition [1]. When most of the cells are old or damaged, they are destroyed and replaced by new cells. If damaged and old cells are not eliminated by generating the new cells, it can cause problems. The production of additional cells often results in the formation of a mass of tissue, which refers to the growth of a tumor. Brain tumor detection is overly complicated and difficult due to the size, shape, location, and type of tumor in the brain.

Diagnosis of brain tumors in the initial stages of the tumor's start is difficult because it cannot accurately measure the size and resolution of the tumor.

In general, diagnosing a brain tumor usually begins with magnetic resonance imaging (MRI). Once MRI shows that there is a tumor in the brain, the most common way to determine the type of brain tumor is to look at the results from a sample of tissue after a biopsy or surgery. And if the tumor is diagnosed and treated early there are high chances of saving patients. Initially, tumor cells are difficult to identify and there are many variations in the sizes of tumors ranging from minor to large-sized. Large-sized tumors are easily detected but small sized tumor detection has the possibility of manual error. In the field of Medical Detection System, MRIs are more advanced and play a vital role.

MRI images provide great accuracy over CT scans. So, the proposed technique has been used by CNN (Convolution Neural Networks) to identify and categorize the tumor from brain images of the brain through MRI images. This neural network can automatically and locally extract the feature from each image. These types of networks consist of neurons with weights and biases that can be learned.

To generalize the results and increase the accuracy with smaller amounts has been made possible through data augmentation. Through these multiple augmented brain tumors and non-tumors, MRI images are generated. It helps in addressing real-world issues in developing a suitable model without overfitting and underfitting has been made possible. And applying normalization, padding, and pooling techniques will decrease computation time. And these techniques are also helpful in increasing model efficiency and decreasing training costs too.

RELATED WORK

An automated method is used to identify and categorize MRI images. This method is based on the Super Pixel Technique and the classification of each Super Pixel. Extremely randomized trees (ERT) classifier is compared with SVM (Support Vector Machine) to classify each super pixel into tumor and normal. This method has two datasets, which are 19

MRI FLAIR images and the BRATS 2012 dataset. The results demonstrate the superior performance of this method using the ERT classifier

Through identifying a tumor using CNN with 3 × 3 small kernels. The method obtained simultaneously the first position for the complete, core, and enhancing regions in dice similarity, coefficient metric (0.88, 0.83, 0.77). CNN is used to simultaneously diagnose MS and normal tumors. CNN was able to accurately classify 98.67% of images correctly into three classes. A multi-stage Fuzzy C-Means (FCM) framework was proposed to segment brain tumors from MRI images

METHODOLOGIES

Dataset:

The data set images used in this paper include brain MRI images of 253 patients, including normal and brain tumors patients who were referred to imaging centers because of headaches. After examination and diagnosis by the doctor, the collected images included brain images of 88 images without brain tumors and 150 images without brain tumor. And to generalize the results, the input datasets are augmented and cropped to identify contours and borders also cropped to identify areas of the brain. After this, the training dataset will become 2000 images to obtain high accuracy. The tumor images are generated with a ratio of 50:50 between non-tumor and tumor brain.

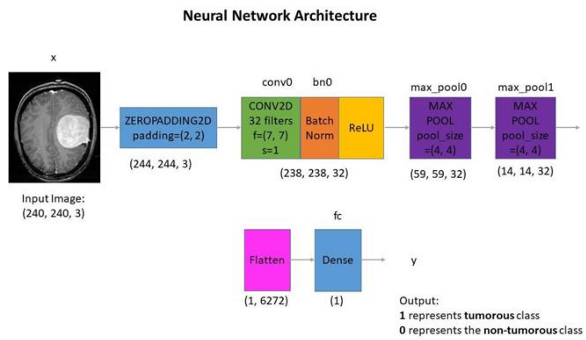
The features are created from the initial dataset. which facilitates the learning process. When the input data of an algorithm is too large, it can be converted to a smaller set of features. The process of extracting a subset from the primary features set is called feature extraction.

Simulation:

Simulation In a few cases, some areas of fat in the pictures are mistakenly detected as tumors, or the tumors may not be seen by the physician; the most exact diagnosis is completely dependent on the physician's skill. In this paper, CNN has been used for tumor detection through brain images. There were additional margins of the images gathered from the imaging centers. These margins were cropped to prevent the noise of the images. One of the main reasons for using the feature extraction technique and combining it with CNN is to retrieve the feature extraction of the images to increase the accuracy of the network. According to the results of the CNN on the initial images, to improve the network accuracy, in this study, a new method which is a combination of Clustering algorithm for feature extraction and CNN is proposed.

CONVOLUTIONAL NEURAL

Convolutional neural method Initially, the images were applied to the CNN without any feature extraction methods. The size of the input images is initially 240 × 240. The adam optimization was used to identify and classify the images, which consisted of 5 Convolutional layers and 3 layers of Sub-sampling layers, Normalization layers, Normalization layers, Fully Connected layers and lastly layer the classification layer. The fully connected layers have 4096 neurons. We have two classes in this layer: brain tumor patient and normal patient. The utilized CNN is shown below



TENSORFLOW LITE MODEL

Convert Brain Tumor models to TensorFlow lite models quickly and easily for mobile-friendly models. With simplicity, it builds machine learning apps for iOS and Android devices. In contrast to server-based architectures, a more effective alternative to mobile model enablement. On mobile devices, it allows offline inference. TensorFlow Lite allows one to execute machine learning models easily on a smartphone, allowing one to perform traditional machine learning tasks without the need for an external API or server. As a result, the models will operate on devices that are not connected to the internet. Models will not be optimized completely so the prediction accuracy while using TensorFlow lite models will always be almost equal to accuracy of the main model. As this model is compatible with mobile platforms it will be less complicated during integration.

Android Integration:
As the model converted has the high potential to detect brain tumors those models will be interactable and will have a high potential and accuracy while predicting. This involves less manual effort and increases the scope and use of the project by allowing users to upload the MRI image of brain in any handheld device. And as those computations optimized for smaller end devices while performing or converting to lite, any kind of device irrespective of OS or platform can operate well with low computing power and low memory capacity devices can also be detected. These help the project to reach and are helpful for many people's daily life. Initially the integrated model should be integrated with android though adding TensorFlow lite Gradle dependencies. This helps in utilizing our converted TensorFlow model.

Interface design & Image conversion:
In order to simplify the process of prediction, the UI design will have an option to select an image from the file explorer and then convert and scaling the image into a dimension of 240 X 240. In order to suit the input format required by our converted tensor flow models, they have to be resized. And then the features are extracted through processing the selected image data with tensor model and the results are used for analyzing

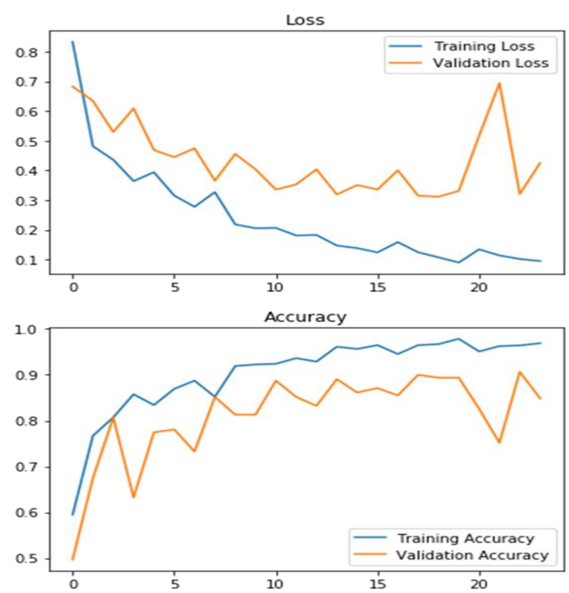
Image Prediction:
After integrating and initializing the model with android app the processed image will be stored in memory as tensor buffer. And those tensor buffers will act as a source of all prediction outputs and features. The output will be of float array and when the first element of array is 1 then the result can be declared as the brain has tumor. And for non-tumor MRI images the result will be 0 obviously. And after analyzing the result the user will be prompted as having brain tumor.

EXPERIMENTAL ANALYSIS

CNN managed to accurately categorize the images into tumor patient and normal patient tumors with a precision of 96.05%. According to the results of the CNN on the initial immature to improve the network performance a combination of the Clustering algorithm for feature extraction and CNN is used.

RESULT

Our Dataset contains tumor and non-tumor MRI images and collected from different online resources. In this work, efficient automatic brain tumor detection is performed by using convolution neural network. Simulation is performed by using python language. The accuracy is calculated and compared with the all-other state of arts methods. The training accuracy, validation accuracy and validation loss are calculated to find the efficiency of proposed brain tumor classification scheme. In the existing technique, the Support Vector Machine (SVM) based classification is performed for brain tumor detection. It needs feature extraction output. Based on feature value, the classification output is generated and accuracy is calculated. The computation time is high and accuracy is low in SVM based tumor and non-tumor detection In the proposed CNN based classification doesn't require feature extraction steps separately. The feature value is taken from CNN itself. Hence the complexity and computation time is low and accuracy is high. The output of brain tumor classification accuracy is given below. Finally, the classification results as Tumor brain or non-tumor brain based on the probability score value. The normal brain image has the lowest probability score. Tumor brain has highest probability score value, when compared to normal and tumor brain.



CONCLUSION

In this paper, a new method based on the combination of the feature extraction algorithm and the CNN for tumor detection from brain images is presented. CNN can detect tumors. CNN is especially useful for selecting an auto-feature in medical images. Images collected at the centers were labeled by clinicians, then, tumor screenings were categorized into two normal and patient classes. A total of 2000images were selected as train data and 226 images were taken as test data. The proportion of image categorization in the two classes was proportional to the ratio of patients to healthy subjects. Images were applied to CNN after preprocessing. To evaluate the performance of CNN, it has been used by other classifiers such as the RBF classifier and the decision tree classifier in the CNN architecture. The accuracy of the CNN is obtained is 88.7%. In addition to the Accuracy criterion, we use the benchmarks of Sensitivity, Specificity, and Precision to evaluate network performance. According to the results obtained from the categorizers, CNN has been able to categorize accurately 88.7% of images in two normal and patient classes. Using the proposed method of feature extraction and applying it to CNN. Due to the importance of the diagnosis given by the physician, the accuracy of the doctors helps in diagnosing the tumor and treating the patient increased high medical accuracy of the proposed method. And also having a client of the android app will have a major advantage of deciding whether the patient has tumor or not.

REFERENCE

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