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Multiclass Brain Tumor Classification Using Transfer Learning

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Abstract

Tumors are a collection of abnormal cells that multiply enormously than required which leads to cancer and divergent and also can be fatal, if not identified at an early stage. Usually, brain scans described as Magnetic resonance imaging (MRI) is deployed for high transparency and representation in different angles but causes huge delay in declaring the result of the test. In this project, images obtained from these tests are carefully observed and classified by implementing Deep Residual Network (RESNET) to classify the type of tumor. There are four types of tumors such as glioma, meningioma, pituitary, and no tumor. Brain tumor classification (Multi Label) – CNN dataset has been imported to train and test the model. This deep learning model is a sophisticated approach which is developed to classify the tumor based on the image, so that appropriate treatment can be given on time. The output determines the type of tumor if present, otherwise no tumor with accuracy of 87% using epochs.

Keywords

Magnetic resonance imaging, deep residual network (resnet), glioma tumor, meningioma tumor, pituitary tumor, deep learning

1. Introduction

The human body is made up of trillions of cells. Generally, human cells multiply as the old ones shed off and new ones replace them. When these cells multiply uncontrollably then it causes cancer. Cancer can be benign and fatal based on its type.

There is no restriction for the growth of cancer. It spreads to any part of the body. This spreading to different body parts is called metastasis. These tissues form lumps or tumors that lead to cancer. According to statistics, about 50% of deaths are due to late diagnosis and delay in identification. This delay leads to an increase in the mortality rate. In India around 28000 of brain tumor cases are identified annually, out of which 24000 cases are deaths. On calculation around 60% of these deaths are caused due to delay in identification.

There are several types of tumors among which pituitary tumor, glioma tumor, meningioma tumor are considered. The former type of tumor develops in the pituitary gland, which is located near the brain, and can affect hormone levels in the body. Pituitary tumors are abnormal growths in the pituitary gland that develop over time. Pituitary tumor can affect the functioning of various hormones as they affect the productivity of that particular hormone. Glioma tumor is also among the regular tumors. This kind of tumor is mostly caused by the glial cells. These cells are non-neural cells but are part of the central nervous system. These cells don't produce any electrical impulses. Glioma tumor effects the functioning of brain such as memory loss, seizures, numbness and many more. A meningioma is a tumor that develops in the membranes that surround the brain and spinal cord, known as the meninges. Although it is not strictly a brain tumor, it is included in this category since it has the potential to compress or pressure the surrounding brain, nerves, and arteries. This type of tumor occurs.

Technology has taken a huge leap where people used to die due to smallpox in ancient times. At present, the medical field has advanced in such a way that cancers are also being treated successfully. Medical devices are implemented to improve the health care in India. These devices play a prominent role in identifying the ailment and treating it with appropriate cure. Artificial Intelligence has been integrated with the health industries to bring treatment at ease. Communication among patients and doctors residing in different parts of the world has helped lots of people in need of placebo. Deep Learning and Artificial neural networks algorithms have been implemented to classify different types of tumors and their categories.

These models have been trained to classify and label the identified illness. These types of models are not only used to classify tumors, but rather in different cases. In this project, the Resnet algorithm has been implemented for image recognition and classification. Resnet model is built with residual blocks. In these types of blocks, the model is trained up to a few layers and other layers are skipped and then redirected to the output. This type of algorithm reduces the complexity of implementing deep residual neural networks.

2. Related Work

A lot of exploration has taken place to classify brain tumors. Detection and classification of brain tumors is a herculean task as the detection of the lumps is complicated. One among them is [1] where to identify brain cancers on MRI scans, a hybrid convolutional neural network is used. In this project several other complex models are also built, and their accuracies are compared to obtaining a highly efficient output. The base is the Resnet50 architecture, which is one of the CNN models. The Resnet50 model's last five layers were deleted, and eight new layers were created in their place. This model achieves a 97.2 percent accuracy level. The Alexnet, Resnet50, Densenet201, InceptionV3 and Googlenet models are also used to achieve results. The brain tumor photos were categorized by the model that performed the best out of all of them.

In Multi grade brain tumor classification [2], a sophisticated CNN model has been built to classify tumors. To begin, deep learning is used to segregate tumor locations from an MR picture. After that, the proposed system is trained using data au mentation, removing the issue related to insufficient data while utilizing MRI for brain tumor classification. At last, improved data fine tunes the pre trained CNN model for grade classification in brain tumor. The proposed system is tested experimentally on both improved data and original data and proves to be more efficient than all the other approaches that are already present.

Deep Learning techniques are used to build a profound model. A convolutional neural network is built to classify brain tumors using two databases [3]. The former database one is used to classify tumors into meningioma, glioma, and pituitary tumor and latter one aims to grade the glioma tumor into Grade II, III and IV. The model produces 96.13 percent and 98.7 percent for either of the databases respectively.

Among all the tumors, glioma tumor [4] is difficult to be classified as it has irregular shape and hard for recognition. Because of the enormous variability in the anatomy of brain tumors, automating their segmentation remains a difficult task. This research presents a deep convolutional neural network (DCNN)-based automated brain tumor segmentation system. From the input images, two co-centric patches have been extracted, from which the deep network is trained with the help of a patch-based procedure along with an inception module. Dropout, batch normalization, non-linear activation, and the inception module are all recent breakthroughs in deep neural networks that have been utilized to create a novel Linear nexus design. Using a dropout regularize, the module solves the over-fitting problem caused by a lack of data.

MRI images are used due to its profound anatomy and these images need human intervention to determine the presence of tumor. A simple model [5] using convolutional neural networks has been built to classify tumors using those images. Different models are used, and the final output is compared to get the most accurate result.

In this suggested technique [6] deep transfer learning associated with a pre-trained VGG16 system for binary classification that focuses to differentiate normal and cancerous MRI images. In comparison to prior traditional approaches, the suggested method achieves a 91.8 percent accuracy and takes less time. To expand the size of the training data set, image augmentation techniques are also applied.

Table 1. Literature survey of Brain tumors using deep learning approaches

S.no	Author	Title	Year	Approach
1	A. Çinar	Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture	2020	Hybrid convolution network such as Resnet50
2	M. Sajjad, S. Khan	Multi-grade brain tumor classification using deep CNN with extensive data augmentation	2019	CNN model
3	H. H. Sultan	Multi-Classification of Brain Tumor Images Using Deep Neural Network	2019	Deep Learning model based on convolutional neural network
4	S. Hussain, S. M. Anwar	Segmentation of glioma tumors in brain using deep convolutional neural network	2018	Deep Convolutional neural network along with dropout regularizer
5	P. Sharma, I. Wahlang	Classification of Brain MRI Using Deep Learning Techniques	2020	Convolutional neural network
6	A. Pundir and E. R. Kumar	Brain Tumor Classification in MRI Images Using Transfer Learning	2021	Deep transfer learning with the ADI of pre-trained model called VGG16 model

3. Proposed Approach

The convolutional neural network model is developed for classification of brain tumors. This model is designed to classify three types of tumors such as glioma tumor, meningioma tumor, pituitary tumor and no tumor. The proposed model has twenty-five weighted layers that include one input, 5 convolutions, 6 Rectified Linear Units, 1 normalization, 5 maxpooling 2D, 2 full connections, six dropouts, one SoftMax and one classification layer. The CNN system is developed to classify images into four sections and hence there are four neurons in the final output layer. It turns out to be a four-dimensional feature vector is sent as input to the SoftMax classifier that presents the final label of type of tumor.

3.1. Convolutional Neural Network

One of the deep neural networks is convolutional neural network that utilizes complex layers to filter input to obtain useful information. The CNN convolutions layer applies its respective filters to the input to obtain local regions of input connected to the output of neurons. Spatial features are features that extract and exploit information from a particular region. Temporal features are the same as spatial features that change as time changes and these can be obtained from CNN model. This system is built with weights that can be treated by calculating the error rate so that the number of parameters can be reduced. CNN is built in three steps, and they are as follows:

(1) A complex layer to study all the spatial and temporal features present in the image.

(2) Amaxpooling2D layer represents the maximum pixel value of the matrix is saved on a output feature map and

(3) A fully connected layer to classify the input image into different classes. The architecture of CNN is shown in the given Figure 1.

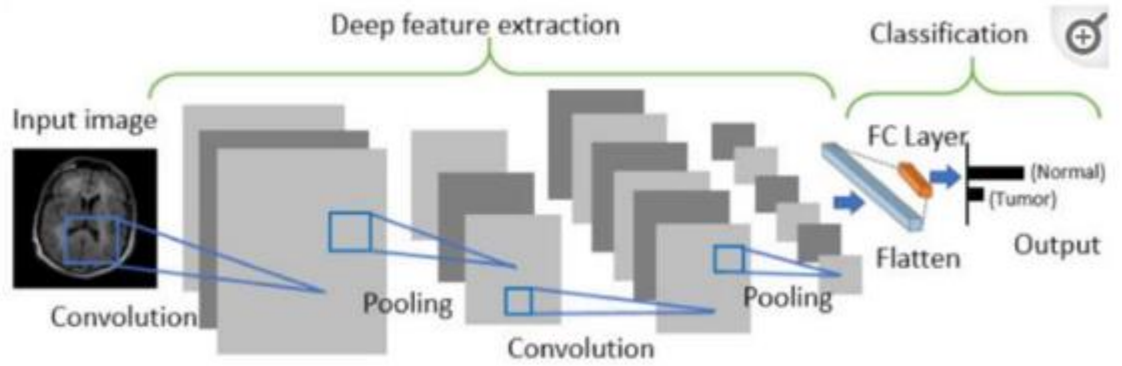

Figure 1. Architecture of Convolution Neural Network

3.2. Image Database

The image database used in this document is provided as a set of slices and contains 3064T1weighted. Contrast-enhanced MRI images are from rider dataset. The version was realized in 2020. There are three types of tumors: meningiomas (708 images), gliomas (1426 images), and pituitary tumors (930 images). All images were taken from 3 233 patients. Figure 2displays various kinds of tumors and various levels. The red frame which is marked is a tumor. The number of images varies from patient to patient. Different levels of tumor types. In the image, the tumor is marked with a red outline.

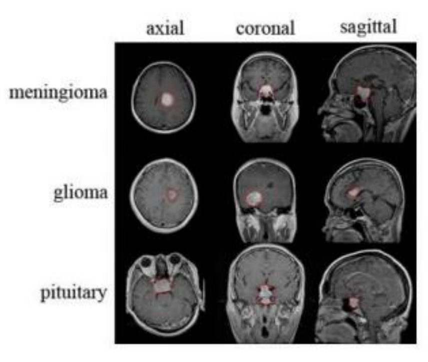

Figure 2. Displaying normalized magnetic resonance imaging (MRI) images using a variety of displays [17]

3.3. Image Pre-Processing

The Magnetic resonance images are standardized and rescaled to 256 x 256 pixels in order to exhibit the enter layer of the network. In the database, magnetic resonance images of various sizes are collected and made available in int 16 format. For the advancement of the dataset, each photograph was converted in several ways. By rotating the photograph ninety degrees, the very first transformation was made. Thus, we intensified our dataset 3 times, subsequently resulting in 9192 pictures by flipping the pictures vertically.

3.4. Feature Extraction

In general, Convolutional neural networks perform better on immense datasets apart from compact datasets. If you are unable to construct a huge training dataset, you can employ transfer learning. Here, a feature extractor based on training the model on a benchmark dataset is applied to an MRI dataset which is a relatively small dataset. Medical image classification and segmentation techniques, as well as x-ray baggage security checks, have successfully used transfer learning techniques in the past few years. As a result, deep learning models can be trained more quickly and do not require large datasets to train.

This significantly reduces the amount of time normally needed to train them from scratch. Deep learning-based feature extraction is applied in this study using a CNN-based model. This is because human administration is not required to capture crucial features. A transfer learning-based approach is also used to generate feature extractors the use MRI datasets since deep CNNs such as ResNet121 are often not trained and tuned from the beginning. In order to extract deep features of brain MR images, we use pre-trained CNN models with fixed weights based on a large ImageNet dataset. Our study used to pre-trained CNN model ResNet. As a traditional deep learning method using CNNs, deep features are extracted and fed to an ML classifier containing a neural network and an FC layer.

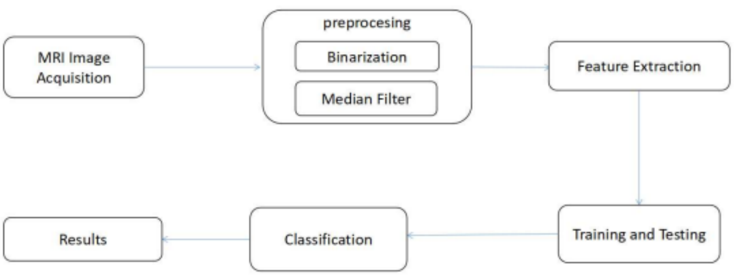

Figure 3. Architecture Diagram of Proposed Work

3.5. Implementation Results

The following are the steps involved in brain tumor classification.

- First take a dataset which contains MRI brain images.
- After taking the MRI Brain images, pre-process the images.
- The pre-processing data will be divided into training and tests.
- The training data will be used to build a classification model.
- After the training we find the validation and training accuracy.
- We use RESENT Algorithm to build the model.
- The testing data is sent into the final model from where the classified brain tumor outputs are obtained.

Experimental Results: After successfully completing the tasks set out. The next step is to take the results at each stage and provide an analysis of the results. The results are shown below. The data frame is divided into training and testing sections. Brain images are shown from the dataset with labels as Glioma Tumor, Meningioma Tumor, Pituitary Tumor and No Tumor.

Sample images of each label: Glioma Tumor: Glioma is a tumor that develops in the brain and spinal cord. Gliomas begin in the gluey supportive cells (glial cells) that surround and support nerve cells.

Meningioma Tumor: A meningioma is a tumor that develops in the membranes that surround the brain and spinal cord, known as the meninges. Although it is not strictly a brain tumor, it is included in this category since it has the potential to compress or pressure the surrounding brain, nerves, and arteries.

Pituitary Tumor: Pituitary tumors are abnormal growths in the pituitary gland that develop over time. Some pituitary tumors cause an overabundance of hormones that control vital physiological functions. Your pituitary gland may generate less hormones as a result of some pituitary tumors.

No Tumor: It means the MRI brain image does not contain any tumor.

And then predicting or labeling the type of tumor for the image.

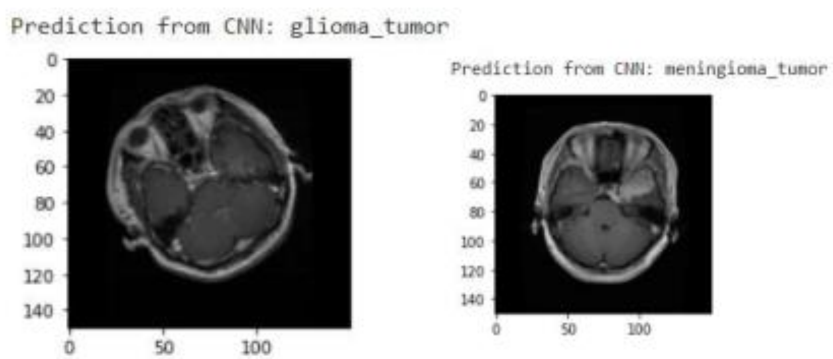

Figure 4. Labelling the Brain Images

The training and validation accuracy was obtained using the Matplotlib library as a graph with the Y axis as the precision. Maximum accuracy is from 87.5% to 95.8% and minimum loss is 0.2957 to 0.8555 with epoch from 25 to 40.

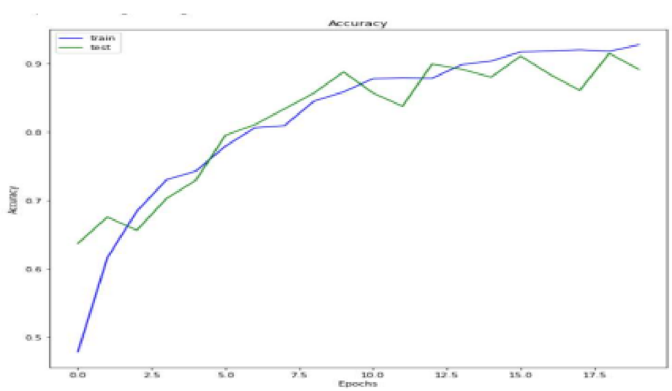

Figure 5. Experimental results graph depicting accuracy

The commonly used calculation measures are:

- Accuracy is the correct portion of the total number of predictions that occurred.
- Accuracy means the proportion of cataloging results that are applicable.
- The recall indicates the proportion of the set of application results that are correctly classified.
- F 1 score indicates the quantity that determines the accuracy of the test
- For Epoch = 10 model gives 75.50% Accuracy
- For Epoch=45 model gives 95% Accuracy

	precision	recall	f1-score	support
0	0.95	0.96	0.95	168
1	0.99	1.00	1.00	108
2	0.97	0.95	0.96	201
3	0.99	1.00	0.99	176
accuracy			0.97	653
macro avg	0.97	0.98	0.97	653
weighted avg	0.97	0.97	0.97	653

Figure 6. Performance metrics obtained

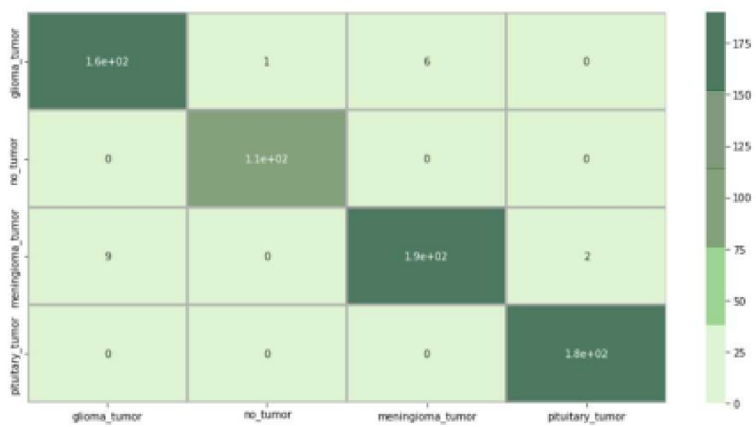

Figure 7. Confusion matrix Obtained between actual and predicted values

4. Conclusion

This model aims to classify different types of brain tumors according to their position in the body. High complex methods can be implemented to classify the tumors in a broader way. Brain tumors can be fatal at times and the only solution is to identify the illness and categorize it. Technology is revolutionizing day by day and these advancements can be implemented to develop the project further. Other updates can also be made to the project by suggesting efficient doctors to get proper treatments. A recommender system can also be added to this project to generate reliable sources.

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