IJARCCE

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 12, December 2021

DOI: 10.17148/IJARCCE.2021.101227

AUTOMATIC BRAIN TUMOR IDENTIFICATION

Prof. Vijay Kumar A[1], Nikhil N[2], Aswin Bharathi K B[3], Palukuri Suptha[4], Pranav J[5]

[1]Professor, [2,3,4,5]Students
Department of Computer Science & Engineering,
Faculty of Engineering & Technology,
JAIN(Deemed-to-be University), Karnataka

Abstract - In a variety of medical diagnostic applications, automated flaw identification in medical imaging has become a hot topic. Automated tumor detection in MRI is vital because it provides information about abnormal tissues, which is crucial for therapy planning. Human inspection is the traditional approach for detecting defects in magnetic resonance brain imaging. Due to the vast volume of data, this strategy is impractical. As a result, reliable and automatic classification techniques are required to reduce the human fatality rate. Because of the intricacy and variety of tumors, MRI brain tumor identification is a difficult undertaking. In this study, we propose employing machine learning methods to overcome the limitations of traditional classifiers in the detection of tumors in brain MRI.

Key Words: MRI, Brain tumor, Convolution Neural Network, Segmentation

1. INTRODUCTION

In the human body, the brain is the most important and significant organ. One of the most prevalent causes of brain dysfunction is a brain tumor. Tumors are nothing more than uncontrolled cell proliferation. Brain tumor cells expand to the point where they consume all of the nutrition intended for healthy cells and tissues, resulting in brain failure. Currently, doctors use MRI pictures of the brain to manually detect the location and extent of a brain tumor. This leads to inaccuracy in tumor detection and is extremely time intensive.

This research is about a system that employs computer-based techniques to locate tumor blocks and classify the type of tumor in MRI scans of various patients using the Convolution Neural Network algorithm. For the detection of brain tumors in MRI scans of tumor patients, several image processing techniques such as image segmentation, image enhancement, and feature extraction are applied. The performance of detecting and categorizing brain tumors in MRI images is improved using image processing and neural network approaches.

2. RELATED WORKS

Dr. P.V.Ramaraju and colleagues devised an algorithm for brain tumor categorization. They employed MRI to detect and classify a tumor in the brain. A wavelet transformation is used in this approach. The wavelet transform is used to extract information from MRI scans of brain tumors. The author used feed-forward probabilistic neural networks (PNN) to categorize brain cancers based on these gathered data. They classified brain MRI into three categories: benign, malignant, and normal.

Meiyan Huang et al. suggested a classification framework for the classical classification model using local independent projection. The authors used a two-spiral structure to evaluate the performance of the proposed LIPC classifier.

According to the National Brain Tumor Society, there are roughly 688,000 persons in the United States who have primary tumors, 138,000 people who have malignant tumors, and 550,000 people who have non malignant tumors (CNS). Despite major breakthroughs in imaging, radiotherapy, chemotherapy, and surgical technique, certain forms of malignant brain tumors, such as high-grade glioblastoma and metastases, remain untreatable, with an 8% at 2.5-year cumulative relative survival rate and 2% at 10 years. Furthermore, patients with low-grade gliomas (LGG) have a mixed prognosis, with a 10-year survival rate of around 57 percent. Previous research has shown that the characteristics of newly discovered brain tumors on magnetic resonance imaging (MRI) can be utilized to predict the likely diagnosis and treatment strategy.

3. PROPOSED SYSTEM

In modern clinical practice, segmentation is still done by hand by human operators. Manual segmentation is a time-consuming job that usually entails slice-by-slice procedures, and the results are highly reliant on the operators' knowledge and subjective decision-making.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 12, December 2021

DOI: 10.17148/IJARCCE.2021.101227

Furthermore, even by the same operator, reproducible results are difficult to achieve. A fully automatic, objective, and repeatable segmentation method is in high demand for multimodal, multi-institutional, and longitudinal clinical research. Medical specialists use magnetic resonance imaging (MRI) data to segment tumors, which is an important but time-consuming manual process.

Because of the wide variation in the appearance of tumor tissues among individuals and their close resemblance to normal tissues in many circumstances, automating this process is a difficult undertaking. To address these concerns, we created a project that automates the process of detecting brain tumor tissues in MRI scans.

Computer-Aided Diagnosis (CAD) systems can offer a highly accurate reconstruction of the original image, giving you a better chance of detecting a brain tumor sooner. It is divided into two or more stages.

Preprocessing is necessary in the first stage, and then post-processing, or segmentation, is required in the second stage. Detection approaches, feature extraction, feature selection, classification, and performance analysis are all compared and analyzed.

4. METHODOLOGY

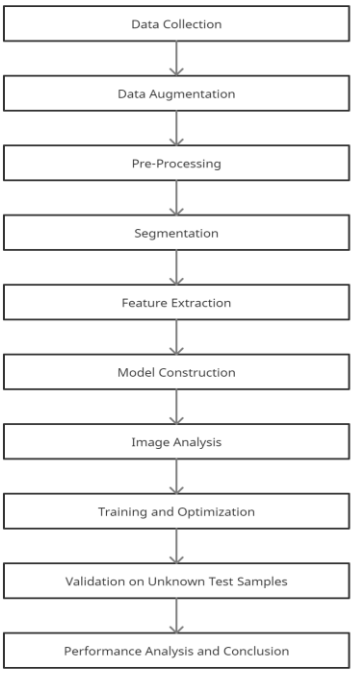

Fig -1: Implementation flow chart

4.1 DATA COLLECTION

Data collection is the initial phase in the tumor identification process, in which we gather the necessary dataset. We used a data set that we found on the Kaggle website. The data is separated into two folders, each labeled with the word "Yes" or "No". Different MRI pictures of the patients may be found in both files. Patients with brain tumors are in the Yes folder, whereas patients without brain tumors are in the No folder. There are 155 photos of brain tumor positive individuals and 98 images of patients who do not have a brain tumor. The photos are all 240X240 pixels in size.

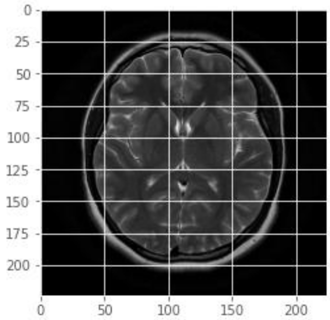

Fig -2: Sample image from data set

IJARCCE

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 12, December 2021

DOI: 10.17148/IJARCCE.2021.101227

4.2 DATA AUGMENTATION

Data augmentation is a strategy for adding slightly changed copies of current data or freshly produced synthetic data from existing data to increase the quantity of data available. By creating extra training data from the original, data augmentation tries to increase network performance. Simple transformations like flipping, rotating, shifting, and zooming can produce displacement fields in pictures, but they won't provide training examples with wildly varied forms. Because tumors have no particular structure, shear surgery can significantly disrupt the global shape of the tumor in the horizontal direction, but it is still insufficient to get adequate varied training data.

4.3 PRE-PROCESSING

One of the prerequisites for real-world data mining challenges is data pre-processing. Data quality suffers as a result of these variables. And if the data is of poor quality, the output of data mining or modeling will be of poor quality as well. As a result, before mining or modeling the data, it must undergo a series of quality-improvement processes known as data pre-processing. The goal of data validation is to see if the information is complete and accurate.

4.4 SEGMENTATION

Image segmentation is a subset of digital picture processing that focuses on dividing an image into distinct portions based on its characteristics and attributes. The basic purpose of picture segmentation is to make the image simpler so that it can be analyzed more easily. The technique of splitting a picture into segments with similar features is known as image segmentation. Image Objects are the pieces of the image into which you split it.

Computer vision implementations would be practically hard for you if you didn't do picture segmentation. To segment and group a certain collection of pixels from an image, we employ several image segmentation techniques.

Image segmentation is an important aspect of computer vision and is utilized in a variety of industries. Face recognition, number plate identification, picture-based search, and medical imaging are just a few of the important domains where image segmentation is widely employed.

4.5 FEATURE EXTRACTION

A feature is a piece of information about the content of an image in computer vision and image processing, usually concerning whether a certain portion of the picture has specific attributes. Specific picture structures, such as points, edges, and objects, can be used as features. The process of defining a collection of features, or visual properties, that will most effectively or usefully represent the information needed for analysis and classification is called feature extraction. The goal of feature extraction is to minimize the amount of features in a dataset by developing new ones from the old ones. The majority of the information contained in the original set of characteristics should then be summarized by these new reduced sets of features.

By extracting features from the input data, feature extraction improves the accuracy of learned models. By deleting unnecessary data, this step of the general framework decreases the dimensionality of data. It does, of course, speed up training and inference. When you have a huge data collection and need to decrease the amount of resources without losing any critical or relevant information, the feature extraction approach comes in handy. Feature extraction aids in the reduction of unnecessary data in a data collection.

4.6 MODEL CREATION & IMAGE ANALYSIS

We build a machine learning model to detect the brain tumor from the photos in the data set in this step.There are two sets of pictures made: one for training and the other for validation. In a 9:1 ratio, the images in the data set are split into training and testing groups. This implies that out of every ten photographs taken, nine are used to train the model and one is used to test it. After that, we add different convents and pooling layers to our network for identifying MRI images.

There are several pre-trained models to pick from in Keras. The state-of-the-art network model VGG16 is being used here to research brain tumors.

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 10, Issue 12, December 2021
DOI: 10.17148/IJARCCE.2021.101227

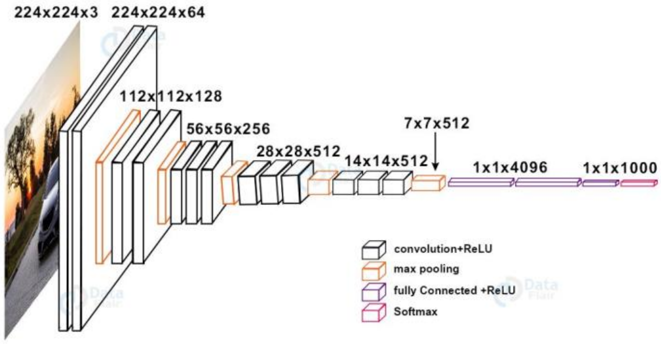

Fig -3: Architecture of VGG16 model

We delete the last layer of the VGG16 network and replace it with layers that are more appropriate for our situation. The layers of our model are frozen in our project. This eliminates the need for the network to be taught from the outset. It continues to train for the layers we built on top of those layers by using the weights from prior layers.The amount of time spent training is substantially reduced as a result of this. We build the model using optimizer as Adam and utilize accuracy metrics to calculate the model's performance after developing the model for recognising the brain tumor in MRI images.

4.7 TRAINING AND OPTIMIZATION

Before training, we went through the architecture of our model. After reviewing the architecture of the model, we now start training our model. Validation on the test data set is also done during this training, and the performance is computed. We also preserve our trained model so that if we perform the training again, it would use the previously trained model and strive to improve it rather than beginning again..

5. RESULTS

After completing the training and validation, we evaluated the model performance using the predict() function.

```
              precision    recall  f1-score   support

          no       0.67      0.60      0.63        10
         yes       0.76      0.81      0.79        16

    accuracy                           0.73        26
   macro avg       0.72      0.71      0.71        26
weighted avg       0.73      0.73      0.73        26

[[ 6  4]
 [ 3 13]]
```

Fig -4: Evaluation results

The model's predictions will be an array, with each value representing the chance that the image belongs to that category. As a result, we choose the highest probability and assign the picture input, that projected label.

The classification report provides a summary of the metrics precision, recall and F1-score for each class/label in the dataset. It also provides the accuracy and how many dataset samples of each label it categorized.

Now, we can find the overall accuracy of the model using the formula: (TP + TN) / (TP + FN + FN + TN). By using the formula it was found that our model has around 96% test accuracy and 73% validation accuracy.

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 12, December 2021

DOI: 10.17148/IJARCCE.2021.101227

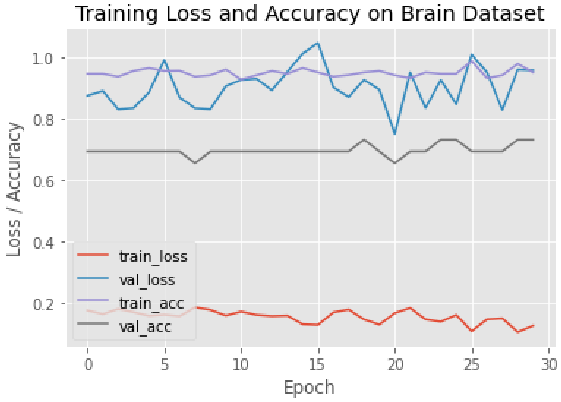

Fig -5: Result graph

6. CONCLUSION AND FUTURE SCOPE

This project created a very thorough framework for best practices in the field of MRI brain imaging methods. Due to the non-invasive and good MRI tissue separation and the use of gathering and collecting methods employing various highlights and spatial imaging in the local region, a substantial number of current cerebrum cell segregation approaches work on MRI images. The goal of these techniques is to offer a basic diagnostic, tumor testing, and therapy decision. And to deliver reliable outcomes in a fair amount of time.

The training accuracy is approximately around 96 percent, however the validation accuracy is just 73 percent in the graph, according to the data in Section 5. The reason for this is because our model doesn't have a lot of photos for validation since we use a 9:1 ratio to separate images in the first place. Due to the pandemic outbreak, we were constrained in our data gathering choices. However, with high-quality MRI pictures obtained directly from scanning centers, we could undoubtedly increase the project's results in the future.

REFERENCES

1. https://bit.ly/3sLGAEb
2. Prachi gadpayle and, p.s. Mahajani, "detection and classification of brain tumour in MRI images ", international journal of emerging trends in electrical and electronics, ijetee – issn: 2320-9569, vol. 5, issue. 1, july-2013
3. https://shorturl.at/eiuxJ
4. http://builtin.com/data-science/transfer-learning
5. Prastawa m., Bullitt e., Greig, g., 2004. A brain tumour segmentation framework based on outlier detection. Medical image analysis 8, 275–283.
6. Goodfellow, Warde-Farley, d., mirza, m., Courville, a., bengio, y., 2013b. Maxout networks, in icml.
7. https://shorturl.at/gCRW4
8. https://shorturl.at/ajstP
9. Erihov, m., Alpert, s., Kiselev, p., Hashoul, s., 2015. A cross saliency approach to asymmetry-based tumor detection. In: medical image computing and computer assisted intervention–miccai 2015. Springer, pp. 636–643.
10. https://arxiv.org/pdf/1409.4842.pdf
11. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6640210

© IJARCCE This work is licensed under a Creative Commons Attribution 4.0 International License