Brain Tumor Detection

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Abstract—Human brain is the major controller of the humanoid system. The abnormal growth and division of cells in the brain lead to a brain tumor, and further growth leads to brain cancer. In the area of human health, Computer Vision plays a significant role, which reduces the human judgment that gives accurate results. CT scans, X-Ray, and MRI scans are the common imaging methods among magnetic resonance imaging (MRI) that are the most reliable and secure. MRI detects every minute object. Our paper aims to focus on the discovery of brain cancer using brain MRI. In this study, we performed pre-processing using the Gaussian filter (BF) to remove the noises in an MRI image. This was followed by the binary thresholding and Convolution Neural Network (CNN) segmentation techniques for reliable detection of the tumor region. Training, testing, and validation datasets are used. Based on our machine, we will predict whether the subject has a brain tumor or not. The resultant outcomes will be examined through various performance examined metrics that include accuracy, sensitivity, and specificity. It is desired that the proposed work would exhibit a more exceptional performance than its counterparts.

Keywords—Convolution Neural Network, Magnetic Resonance Imaging

I. INTRODUCTION

Medical imaging is the technique and process of creating visual representations of the interior of a body for clinical analysis and medical intervention, as well as visual representation of the function of some organs or tissues. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. The early detection and treatment of brain tumor helps in early diagnosis which aids in reducing mortality rate. Image processing has been widespread in recent years and it has been a most important part in the medical field also. The abnormal growth of cells in the brain causes brain tumour. Brain tumor can be detected by the diagnostic imaging modalities such as CT scan and MRI. Both of the modalities have advantages in detecting depending on the location type and the purpose of examination needed. Brain Magnetic Resonance (MRI) is a very familiar medical activity that is used for analysis and diagnosis of many neurological diseases. In this paper, we prefer to use the MRI images because it is easy to examine and gives out accurate calcification and foreign mass location. Noises present in the Brain MRI images are multiplicative noises and reductions of these noises are difficult tasks. The minute anatomical details should not be destroyed by the process of noise removal from a clinical point of view. This makes accurate segmentation of brain images a challenge. However, accurate segmentation of the MRI images is very important and crucial for the exact diagnosis by computer aided clinical tools. Magnetic resonance imaging is a noninvasive medical test that helps physicians diagnose and treat medical conditions.MRI uses a powerful magnetic field, radio frequency pulses and a computer to produce detailed pictures of organs, soft tissues, bone and virtually all other internal body structures. The images can then be examined on a computer monitor, transmitted electronically, printed or copied to a CD. MRI does not use ionizing radiation (x rays). Detailed MRI images allow physicians to evaluate various parts of the body and determine the presence of certain diseases. Brain Magnetic Resonance (MRI) is a very familiar medical activity that is used for analysis and diagnosis of many neurological diseases.

II. RELATED WORK

Image segmentation and classification is one of the major tasks in machine learning and it is widespread in clinical diagnosis also. Medical image segmentation for detection of brain tumor from the magnetic resonance (MRI) images or from other medical imaging modalities is a very important process for deciding right therapy at the right time. Many techniques have been proposed for classification of brain tumors in MRI images, most notably, fuzzy clustering means (FCM), support vector machine (SVM), artificial neural network (ANN), knowledge-based techniques, and expectation-maximization The Author [1] Deep learning (DL) is a machine learning subfield that has recently shown promise, particularly in classification and segmentation tasks. This research proposes a convolutional neural network-based deep learning model. To categorize distinct forms of brain tumors, a network is built using two publically available datasets. The first is correct; tumors are divided into three categories (meningioma, glioma, and pituitary tumor). The other differentiates between the three types of glioma (Grade II, Grade III, and Grade IV). There are 233 and 73 patients in the two datasets, respectively. T1 has 3064 photos, whereas T2 only has 516.The two trials had a total accuracy of 96.13 percent and 98.7 percent, respectively. The Author [2] To produce a generic and comprehensive method for neural network acceleration, develop a Wavelet-like Auto-Encoder (WAE) that decomposes the original input picture into two low-resolution channels (sub-images) and includes the WAE into the classification neural networks for joint training. The two deconstructed channels, in particular, are encoded to convey low-frequency (for example, picture profiles) and high-frequency (for example, image features or sounds) information, allowing the decoding process to reconstruct the original input image. To obtain the classification result, the low-frequency channel is fed into a conventional classification network like VGG or Res Net, while the high-frequency channel is fused with a very lightweight network. The Author [3] An artificial brain tumor segmentation method based on texture features and kernel sparse coding from FLAIR contrast-enhanced MRIs is presented in this study. To reduce noise, improve contrast, and rectify intensity non-uniformity, the MRIs are initially pre-processed. The first and second order statistical eigenvectors acquired from original MRIs, which is a patch of 33 surrounding the voxel, are sparsely coded after that. To generate two adaptive dictionaries for healthy and sick tissues, kernel dictionary learning is utilized to extract non-linear characteristics. The voxels are coded using a kernel-clustering approach based on dictionary learning, and the target pixels are classified using the linear discrimination method. Finally, the flood-fill process is employed to increase the quality of the segmentation. The findings show that the method works. The Author[4] Image segmentation is the process of dividing an image into usable pieces for a certain application. A photograph's edge is both a fundamental and distinguishing feature. Recognizing edges is one of the most important aspects of image processing in order to continue processing. The technique of locating and distinguishing sharp items is known as segmentation. This paper makes use of a brain image. To aid in the identification of the document's specific content, the territory of interest is first located for the purposes of analysis and detection. The detection of edges uses morphological processes at their most fundamental level. This is why thresholding is employed. The Author [5] Many medical applications including 3D visualization, computer-aided diagnosis, measurements, and registration require image segmentation. This research report has presented a high-level overview of the essential ideas of the use of MRI to segment the human brain and methods for doing so this term is frequently used. New application-specific segmentation challenges emerge as a result of the rapid growth of medical picture modalities, and new approaches are constantly researched and developed, introduced. Choosing the right technique for the job, developing a specific application is a demanding task. A lot of the time, a to get, a combination of procedures may be required, the purpose of segmentation.

III. PROPOSED WORK

Brain Tumor Detection by using Convolutional Neural Network categorization of brain MRI images for illness diagnosis. The majority of the images gathered are in MRI format, which is an imaging technology that produces three dimensional detailed anatomical images.

A. Image Acquisition

For the investigation of brain tumour identification, many bio-medical imaging records are available. Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) are two common approaches (MRI). The theory behind MRI is that both a magnetic field and radio waves can be used to create an image of the interior of the human body. MRI has a better resolution and contains rich information. The MRI dataset from Navoneel Chakrabarty's kaggle was used in this study. There are 98 normal brain images and 155 unnormal brain photos in this book. 'Yes' denotes tumour images, while 'No' denotes healthy images in this dataset. In order to increase the quantity of samples, the augmentation procedure is used. Rotation, modifying width shift range, height shift range, and brightness range of horizontal and vertical flip are all included in the augmentation stage.

B. Preprocessing

Before an image given as input to a model, preprocessing has to be done as an initial step, which means removal of noise by the processes of gray scaling, thresholding and blurring.

- Gray scaling

  To begin, convert RGB Mri images into grey for the goal of gray scaling, the most frequent image processing technique, because a small amount of data allows users or developers to perform more sophisticated operations in less time.

- Thresholding

  Each image has particular threshold value .By using thresholding convert an image into binary .We most commonly utilize thresholding to choose areas of interest in an image while ignoring the sections we don't care about.

- Gaussian Blur Filter

  The technique of blurring an image is one of the most significant components of image processing since it reduces the amount of noise in the image. A Gaussian blur filter is created using this method. The radius is a parameter in the filter, and it is controlled by Changing the radius's value changes the intensity of the light. The blurriness of the image is altered. Radius is a parameter. The blur intensity is controlled by the function. By altering the radius's measurement, Gaussian Blur’s intensity is altered.

For every image, the following preprocessing steps were applied:

1. Crop the part of the image that contains only the brain.
2. Resize the image to have a shape of (240, 240, 3). So, all images should have the same shape to feed it as an input to the neural network.
3. Apply normalization.

Firstly convert RGB images to gray for the purpose of preprocessing of images by grayscaling,most commonly used in image procesing,because small amount of data enables users or developers to do more complex operation in a shorter time.

C. Morphological Operations

Morphological operations apply a structuring element to an input image, creating an output image of the same size. In a morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.The Morphological techniques are also used with segmentation techniques. The morphological action is normally performed on binary images. It processes the operations based on shape and it has a wide set of the image processing operation.Erosion and Dilation are two methods of morphological operations which used in this proposed work. We perform both Erosion and dilation operations used together.Two main steps of the erosion and dilation morphological operation are opening and closing. The first step is the opening of the MRI binary image. The main work of opening operation is open up a gap which is present in between object and connect that to a small collection of pixels. After setting of the bridge, the erosion again restored with their actual size using dilation. If the binary image has been opened then the subsequent opened same structured elements have not affected on that image. After completing the opening operations next step is the closing operation. Based on the closing operation while keeping the original region sizes, the erosion and dilation can handle different hole in the image region. Dilation and Erosion are the basic morphological operations. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries.To improve the output and develop the CNN, additional steps are needed. This involves overfitting correction, data augmentation, pooling, and the application of rectified linear unit (ReLU). Further details are below:

Overfitting refers to the fact that the neural network may be overtrained to the training dataset and produce inferior segmentations. To account for this, the CNN needs to be trained somehow to recognise imprecise features of the input. Four example methods are described. These are data augmentation, dropout, batch normalisation, and pooling.Data augmentation can be used to generate imprecise inputs. Similar to the software used to edit photographic images, MRI images can be cropped, zoomed, and rotated [18]. This reduces overfitting as the neural network will not recognise specific patterns within the input dataset based on morphological arrangements which are deemed irrelevant between images. Dropout is a method whereby nodes are temporarily ‘dropped’ in the convolutional neural network in order to produce imprecision within the dataset. Batch normalisation is a method employed to reduce the weighting power of nodes that have a high bias. This allows for generalisability on other datasets as these high weights may be associated with specific precise features within the training set.Pooling is where the input image is down sampled or the resolution is degraded in order to train the CNN to identify features that are imprecise. In other words, it reduces the chance of the network identifying insignificant details.

D. Brain Tumor Image Classification Using Convolutional Neural Network

Classification is the best approaches for identification of images like any kind of medical imaging. All classification algorithms are based on the prediction of image, where one or more features and that each of these features belongs to one of several classes. In the field of medical image processing, convolutional neural networks are widely employed. Many academics have tried over the years to develop a model that can more accurately detect tumours.The convolution layer, the pooling layer, the flatten layer, the dropout layer, and the dense layer are all layers in the CNN model. Assembled the model and determined the accuracy of recognising the tumour using Adam optimizer and binary cross-entropy as a loss function.

```
Model: "BrainDetectionModel"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 240, 240, 3)]     0

 zero_padding2d (ZeroPadding  (None, 244, 244, 3)      0
 2D)

 conv0 (Conv2D)              (None, 238, 238, 32)      4736

 bn0 (BatchNormalization)    (None, 238, 238, 32)      128

 activation (Activation)     (None, 238, 238, 32)      0

 max_pool0 (MaxPooling2D)    (None, 59, 59, 32)        0

 max_pool1 (MaxPooling2D)    (None, 14, 14, 32)        0

 flatten (Flatten)           (None, 6272)              0

 fc (Dense)                  (None, 1)                 6273

=================================================================
Total params: 11,137
Trainable params: 11,073
Non-trainable params: 64
```

Fig 1 : CNN Model Summary

IV. EXPERIMENTAL AND MODEL EVALUVATION

A. Experimental Set Up

The model has been validated using various experimental results obtained from the dataset in question. The Python 3.6 platform was used for the experiment, along with some fundamental tools like as NumPy, scilpy, and matplotlib. In addition, data analysis software such as keras, scikit-learn, and tensor flow were installed on an i7 core processor with a 3.4 GHz speed and 4 GB RAM.

B. Dataset Description

The Brain MRI Images for Brain Tumor Detection dataset was obtained from kaggle.com. The collection contains 253 images divided into two categories: 155 brain images with tumors and 98 brain images without tumors.

V .RESULTS AND DISCUSSION

Images consisting of samples containing 155 Brain MRI Images that are tumorous and the folder no contains 98 Brain MRI Images that are non-tumorous. The data is further divided into 70% of the data as data training, 15% of the data as data validation, 15% of the data as data testing. The data is run 5 times, each using the CNN model that has been made before, each experiment using 10,5,3,3 epochs etc. with the accuracy of 92%. Accuracy, Specificity, Sensitivity, and F-Score are the four criteria used to evaluate performance. It has been empirically proven that the CNN technique outperforms other classic non-deep learning techniques. It can be seen that the CNN Model technique has a significantly higher accuracy than the T algorithms, as well as a higher specificity, sensitivity, and F-score measure than the previous two. state the units for each quantity that you use in an equation.

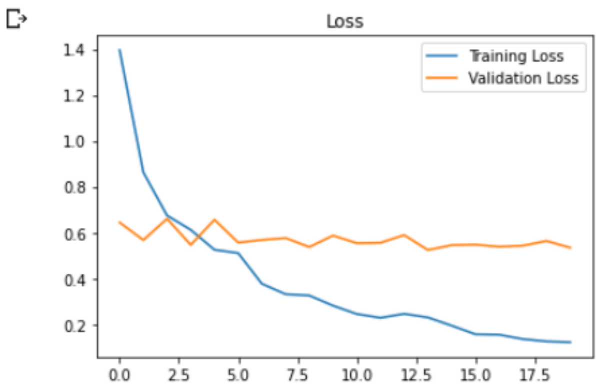

Fig 2 :Training Loss & Validation Loss

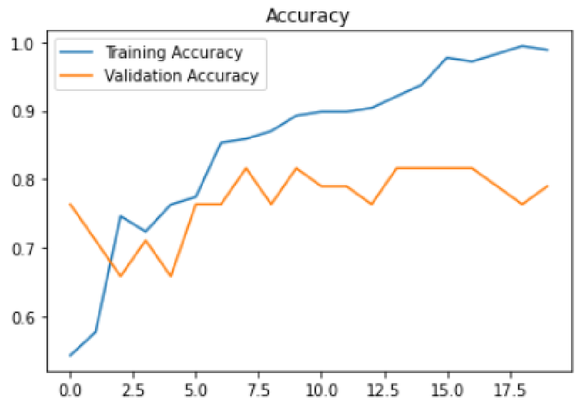

Fig 3: Training Accuracy & Validation Accuracy

The MRI pictures must first be preprocessed in order to retrieve images from the dataset; following that, all images are displayed in a 2-D array format. These two-dimensional arrays are flattened once more to represent all photos in a two-dimensional dataset format. Because the number of photos is so large, they've been divided into a lot of small sub arrays for improved performance. The encoded images are then obtained by processing these image sub arrays with DWA. Brain MRI pictures were preprocessed by extracting them into a specific image matrix, flattening them, and splitting them into subarrays for encoding using a deep wavelet autoencoder

VI. Conclusion

Medical picture dataset interpretation has always been a time-consuming procedure, and handling them is a difficulty in and of itself. CNN model has produced excellent results in terms of accuracy, specificity, sensitivity, and other performance measures. Technique's results reveal that it outperforms all existing non-deep learning strategies in terms of accuracy and statistical measures. It would be significantly more fascinating to investigate the effects or performance of mixing with a variety of variations in the same brain MRI dataset.

VII FUTURE SCOPE

It is observed on extermination that the proposed approach needs a vast training set for better accurate results; in the field of medical image processing, the gathering of medical data is a tedious job, and, in few cases, the datasets might not be available. In all such cases, the proposed algorithm must be robust enough for accurate recognition of tumor regions from MR Images. The proposed approach can be further improvised through in cooperating weakly trained algorithms that can identify the abnormalities with a minimum training data and also self-learning algorithms would aid in enhancing the accuracy of the algorithm and reduce the computational time.

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References

[1] H. H. Sultan, N. M. Salem, and W. Al-Atabany, “Multi-classification of brain tumor images using deep neural network,” IEEE Access, 2019.
[2] T. Chen, L. Lin, W. Zuo, X. Luo, and p. a. y. . Zhang, Lei title = Learning a Wavelet-like Auto-Encoder to Accelerate Deep Neural Networks.
[3] J. Tong, Y. Zhao, P. Zhang, L. Chen, and L. Jiang, “Mri brain tumor segmentation based on texture features and kernel sparse coding,” Biomedical Signal Processing and Control, vol. 47, pp. 387–392, 2019.
[4] A. Jyoti, M. N. Mohanty, and M. Pradeep Kumar, “Morphological based segmentation of brain image for tumor detection,” in 2014 International Conference on Electronics and Communication Systems (ICECS), 2014, pp. 1–5.
[5] I. Despotović, B. Goossens, and W. Philips, “MRI segmentation of the Human Brain: Challenges, Methods, and Applications,” Computational and Mathematical Methods in Medicine, 2015.