BRAIN TUMOR ANALYSIS AND DETECTION USING DEEP LEARNING TECHNIQUES

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Abstract— **A brain tumor is an abnormal growth of cells inside the brain or skull, some are benign, others malignant. Diagnosis and treatment will be applied depending on the tumor type, size and location. Therefore, we proposed a modified computer aided diagnosis system that detect tumor conditions, the types of tumors. The Recurrent Neural Network and Convolutional Neural Network (RNN+CNN) architecture is proposed in this research coupled with a three-step preprocessing method to improve the quality of MRI images for use in diagnosing gliomas, meningiomas, and pituitary tumors. The architecture makes advantage of batch normalization for quick training, a greater learning rate, and simple layer weight initialization. 99.27% accuracy is attained overall. The MRI dataset from Kaggle is used to evaluate the recommended model. The proposed system will be developed using python.**

Keywords: Brain tumor, machine learning, deep learning, thresholding, histogram equalization, recurrent neural network, radial basis function networks.

I.INTRODUCTION

The majority of human behaviors, including memory, speech, thought, and leg and arm motions, are controlled by the brain, which is the principal component of the human body. The majority of brain diseases are brought on by aberrant brain cell proliferation, which directly harms the brain's structure and causes brain cancer. Records from the World Health Organization (WHO) show that cancer claimed the lives of nearly 9.6 million people worldwide [1]. Brain cancer is lethal, fast spreading, and dangerous. Furthermore, the complexity of the brain's development presents a significant hurdle, necessitating prompt and correct diagnosis. Better contrast and particular definition can be seen with magnetic resonance imaging (MRI) [2]. To ascertain whether or not there are abnormalities in an MRI image, the method of detecting brain abnormalities is crucial. Deep Learning is being used by researchers in a variety of medical science fields. We are developing a computer-aided method for brain tumor diagnosis using Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) because there is currently no integrated model to produce more accurate results. In the project, an effective deep diagnosis method is proposed (Figure 1). Here are some details regarding the paper contribution:

- As a starting state, a three-step pre-processing procedure is suggested.
- By using this technique, MRI pictures' quality and contrast are improved.
- The combined RNN and CNN architecture is utilized to determine tumor and its types.
- Batch normalization [15] is applied to train the model faster and get a higher learning rate.

We organized the rest of the paper as follows: First section II discusses the related work, secondly, section III describes the applied methodologies in this paper, thirdly section IV shows the experimental result, then section v presents the concluding remarks.

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II. LITERATURE REVIEW

There have been a lot of studies and researches recently about finding brain tumors in MRI pictures.This section examines a number of credible works Bahadureetal.[3]. Investigated through Berkeley wavelet transformation (BWT) ba sed brain tumour segmentation to enhance efficiency while redu cing complexity in the medical image segmentation process.Rele vant features are also extracted from each segmented tissue to in crease the support vector machine (SVM) based classifier's accu racy and quality rate.Based on accuracy, sensitivity, specificity, and dice similarity index coefficient, the experimental findings o f the suggested technique have been assessed and validated for p erformance and quality analysis on magnetic resonance brain im ages.The testing results showed 96.51% accuracy, 94.2%specific ity, and 97.72% sensitivity, proving that the suggested technique for distinguishing between normal and pathological tissues from brain MR images works. Pereira et al.[4]explained that Brain tumour segmentation is significant in medical image proce ssing.It is crucial to identify these tumourseearly in order to treat patients.The earlier it is discovered, the better the patient's chanc es of survival.It takes time and is challenging.Enhanced Convolu tional Neural Networks (ECNN) with loss function optimisation using BAT algorithm for automatic segmentation method are su ggested as a potential fix to these issues.Putting forward optimiz ationbased MRI picture segmentation is the desired outcome. Varthanana et al. [5] provided a technique for detecting brain cancers utilizing a new self-organizing map (SOM) and Fuzzy K-Mean (FKM). Their segments outcomes have been verified by knowledgeable radiologists. Unfortunately, their suggested strategy is complicated and laborious with actual useful applications. Dhanachdra et al. [6] suggested a method to enhance the quality of MRI pictures. Their method uses an arbitrary approach to compute the cluster centre's starting value. To improve the quality of the supplied image, they utilized another contrast stretching algorithm. Although they also employed the K-mean technique, the categorization process was not accurate enough. Varana et al. [7] based on a brain aberrant region, Discrete Wavelet Transform (WDT) was employed. To find brain cancers in the MRI scans, they investigated a Probabilistic Neural Network (PNN). Sachdera et al.[8] suggested a PCA-ANN (Principal Component Analysis-Artificial Neural Network) for the categorization of various types of brain tumors. The ROIs they receive from the Content-Based Contour are numerous (CBAC). The results of their trials revealed a respectable improvement in accuracy, going from 77% without PCA to 91% with PCA. Corso et al.[9] combined a graph-based affinity method with a generative model-based strategy to present an automatic segmentation solution. Using a weighted aggregation approach, their model was added to multi-level segmentation. Abiwinanda et al. [10] used a convolutional neural network to study three prevalent types of brain malignancies, including glioma, meningioma, and pituitary tumors (CNN). From a hidden layer, convolution, max-pooling, and flattening layers are used in turn with the full connection to build CNN. The 3064 T-1 weighted Contrast-Enhanced Magnetic Resonance Imaging (CE-MRI) images used in the CNN training for the analysis of brain tumors are available via figshare Cheng. The basic architecture was used to achieve training accuracy of 98.51% and validation accuracy of 84.19% without the need of any prior region-based segmentation, in contrast to more complex region-based segmentation algorithms, whose accuracy ranges from 71.39% to 94.68% on the same dataset. Pashaei et al.[11]proposed an Extraction of hidden characteristics from images using CNN and the Kernel Extreme Learning Machine was demonstrated (KELM). In T1-weighted CE-MRI pictures, the various types of brain tumors—including meningioma, glioma, and pituitary tumors—are combined to assess the predicted system's performance. When compared to other classifiers that produce better results, such as Support Vector Machine and Radial Base Function, the CNN and KELM(KE-CNN) combo outperforms them. Gopi et al. [12] By using the two common categories of tumors, benign and malignant, for clustering-based categorization, the research work produces improved clustering outcomes. The GLCM approach was used to extract features, while FCM, Fast FCM, and the k-means algorithm was used to segment the images. The suggested PSO-based RBFN model has demonstrated the possibility of tumor clustering. The study work's key contribution is the automatic identification and classification utilizing the suggested RBFNN model with PSO-WCA training. In comparison to the other features, the feature variance played a significant influence in clustering categorization. Kurtosis with variance, skewness with variance, and energy with variation from the feature variance have provided satisfactory classification results. Sivasai et al. [13] suggest Put your attention on the usage of several methods for finding brain cancer utilizing brain MRI. In this study, we used the Adaptive Bilateral Filter (ABF) for pre-processing to get rid of the sounds that are present in an MR image. Then, for accurate tumor region recognition, the binary thresholding and Fuzzy Recurrent Neural Network (FR-Net) segmentation algorithms were used. The inceptionv3 model's deep features[16] are retrieved and us ed t distinguish between pituitary tumours, gliomas, meningio mas, and no tumours using a score vector obtained by softmax and fed into the quantum variational classifier (QVR).The clas sified tumour photos have been sent to the suggested Segnetw ork, where the real infected area is subdivided to assess the tu mour severity level.On three benchmark datasets, including Ka ggle, 2020BRATS, and locally gathered photos,the results of t he research that was reported were reviewed.The proposed mo del's efficacy was demonstrated by the model's detection score s of better than 90%.

The proposed system begins by reading the MRI image from the dataset, followed by a three-step image pre-processing procedure to improve the quality of the MRI image and a reliable combined network (RNN+CNN) for precisely detecting brain tumors.

III.METHODOLOGY

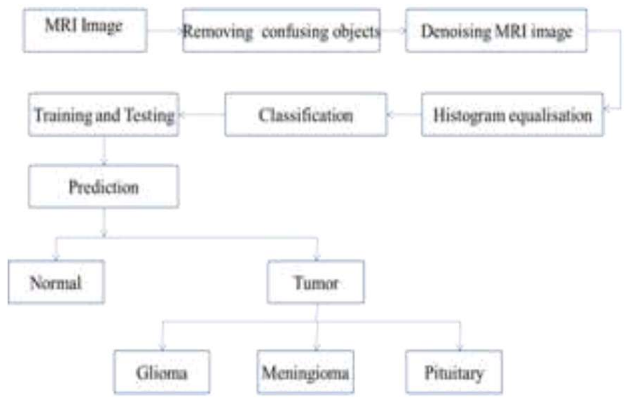


Figure 1. Block Diagram

A. THE PROPOSED PRE-PROCESSING APPROACH

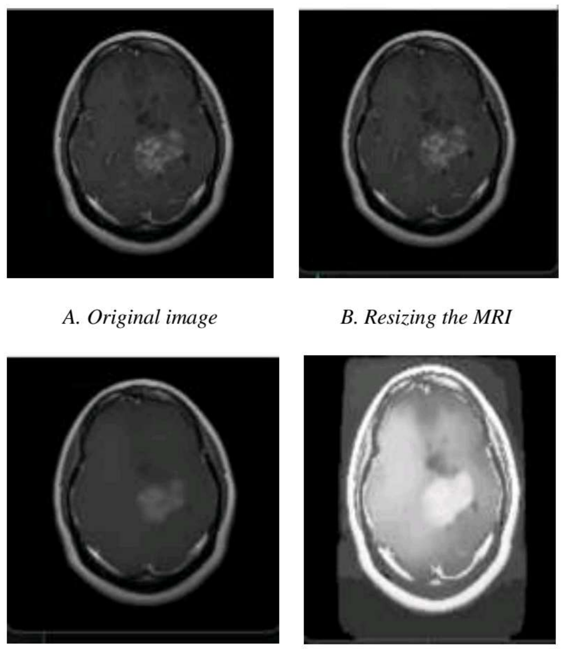
Finding the right pattern is the key to successfully classifying the brain tumor in MRI pictures, according to a classification challenge. The classification models in MRI images must deal with a number of difficulties, which might result in mislearning and lower classification accuracy ratings. Thus, we suggested a three-step pre-processing strategy.

1) REMOVING THE CONFUSING OBJECTS

Then the first step is to remove the confusing objects from images which helps to improve the quality of an image after removing irrelevant image data from image in various applications and domains. Medical images contain lot of irrelevant and unwanted parts in its actual format of the scanned images. To remove such annoying parts in an image, it is required some of the image preprocessing techniques in order for better visualization of the images before finding the diseases in particular. This step provides a fast and accurate means to predict the location of an unwanted object in an image. By subtracting 100 pixels from either side of the image, confusing elements like letters and the dark corners on the right and left have been removed to reveal the precise brain object in figure 2(B).

2) DENOISING THE MRI IMAGES

Medical images often consist of low-contrast objects corrupted by random noise arising in the image acquisition process. Thus, image denoising is one of the fundamental tasks required by medical imaging analysis. Recently non-local means has been extended to other image processing applications such as de-interlacing, view interpolation, and depth maps regularization. The Non-local Mean Algorithm (NLM) effectively reduces noise in MRI images. The noise in these images causes unfavourable patterns to be learned, which lowers the classification accuracy. The MRI images' quality is significantly improved by the NLM algorithm.



A. Original image *B. Resizing the MRI*

C. Denoising *D. Histogram Equalization*

Figure 2. Image Pre-processing

3) HISTOGRAM EQUALIZATION

Histogram Equalization techniques help to enhance the image so that it gives an improved visual quality and a well defined problem. The contrast and brightness is enhanced in such a way that it does not lose its original information and the brightness is preserved. Image histograms are an important tool for inspecting images. They allow you to spot Back Ground and grey value range at a glance. Also clipping and Quantization Noise in image values can be spotted immediately. The contrast in the MRI pictures is greatly enhanced by histogram equalization . Also, by setting zones with lower contrast and suitable contrast, it enables the detection of small details. It completes this procedure by executing a separation to the intensity values with the highest frequency. Also, as seen in figure 3, it removes the interference of the most prevalent patterns in the MRI scans.

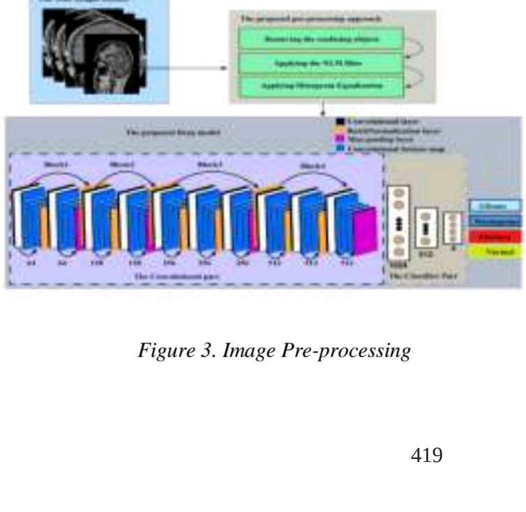


Figure 3. Image Pre-processing

B. DATASET

The brain MRI pictures dataset [14] from kaggle served as the foundation for the dataset that was used in the experiments and tests. There are 2870 photos in the input dataset. Glioma 826, meningioma 822, and pituitary 827 are three of the 2475 tumour photos in this dataset, along with 395 non-tumor images. In the original dataset on Kaggle, the non-tumor photos folder's name was "no_tumor." After pre-processing the photos, a 70%–30% split was used to separate the training dataset from the validation dataset. Pre-processing steps included histogram equalization, scaling, denoising, and the removal of distracting elements.

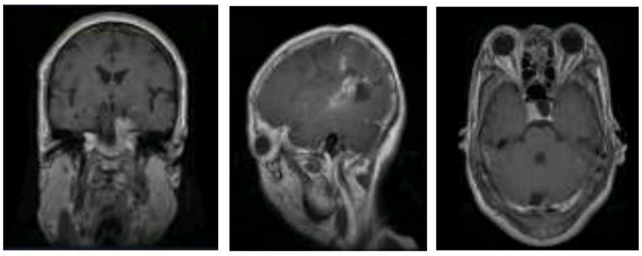


Figure 4. Shows three types of tumors(Meningioma Glioma tumor, pituitary)

C.THE PROPOSED MODEL

In this paper, a hybrid RNN/CNN architecture is proposed. Recurrent Neural Networks (RNNs) are a type of neural network in which the results of one step are fed into the next step's computations. Traditional neural networks have inputs and outputs that are independent of one another, but there is a need to remember the previous words in situations where it is necessary to anticipate the next word in a sentence. As a result, RNN was developed, which utilized a Hidden Layer to resolve this problem. The Hidden state, which retains some information about a sequence, is the primary and most significant characteristic of RNNs.

Convolutional Neural Networks (CNNs, or ConvNets) are a type of artificial neural network (ANN) used most frequently in deep learning to analyze visual data. Based on the shared-weight architecture of the convolution kernels or filters that slide along input features and produce translation-equivariant responses known as feature maps, CNNs are also known as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN). Contrary to popular belief, most convolutional neural networks do not translate invariantly because of the down-sampling operation they perform on the input. They have uses in the recognition of images and videos, recommender systems, classification and segmentation of images, analysis of images used in medicine, natural language processing, brain-computer interfaces, and financial time series.

Multilayer perceptrons are modified into CNNs. Fully linked networks, or multilayer perceptrons, are those in which every neuron in one layer is connected to every neuron in the following layer. Due to their "full connectivity," these networks are vulnerable to data overfitting. Regularization techniques that prevent overfitting often involve reducing connectivity or penalising training parameters. By utilizing the hierarchical structure in the data and assembling patterns of increasing complexity utilizing smaller and simpler patterns imprinted in their filters, CNNs use a different strategy for regularization. CNNs are therefore at the lower end of the connectivity and complexity spectrum. This proposed model resolves many issues such as decreasing the overfitting, slow learning rates and lack of training accuracy.

1) CNN+RNN Architecture

We will employ a CNN combined LSTM based deep learning architecture. The CNN LSTM architecture combines LSTMs for sequence prediction with Convolutional Neural Network (CNN) layers for feature extraction from input data. A CNN LSTM can be created by first adding CNN layers, then LSTM layers, and finally a Dense layer at the output. We must put together the deep learning architecture with assigned loss functions and optimizers after generating the model.

2). Training

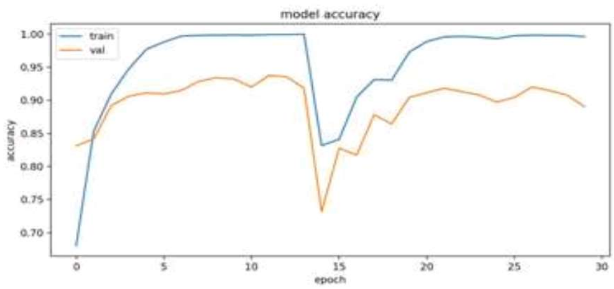
We will use the train set to train our CNN LSTM model and the test set to validate it. Following that, we will calculate the accuracy and save the trained model.

3). Prediction

First, we will read the MRI image using the cv2 library, resize it, perform denoising and histogram equalisation on it, then load the trained model. After loading the model, the pre-processed image will be input to the model, and the model will predict whether the person has a brain tumour (Glioma/Meningioma/Pituitary) or not.

IV. EXPERIMENTAL RESULT

The model has been implemented using Python and Kera library on TensorFlow , Google Colaboratory note along with Github where the used dataset is uploaded . We hired the train part of the used dataset in the training process. Figure 5 shows the training accuracy and the training loss of the proposed model along with the discussed models.



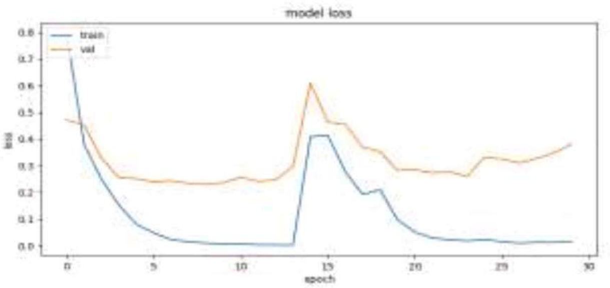


Figure 5: The Training accuracy and Training loss .

As you can see in the diagram, the accuracy increases rapidly in the first five epochs, indicating that the network is learning fast. Generally, if the training data accuracy keeps improving while the validation data accuracy gets worse, if data are encountering overfitting. It indicates that the model is starting to memorize the data. At training, we get 99%, and at validation, we get 93%. The loss on the training set decreases rapidly for the first five epochs. For the test set, the loss does not decrease at the same rate as the training set, but remains almost flat for multiple epochs. This means our model is generalizing well to unseendata.A measurement used to evaluate how well a deep lea rning model fits the training data is called training loss.

A confusion matrix is a table that is used to define the performance of a classification algorithm. A confusion matrix visualizes and summarizes the performance of a classification algorithm. Classification accuracy alone can be misleading if you have an unequal number of observations in each class or if you have more than two classes in your dataset.A multi-class confusion matrix here that is pituitary_tumor, no_tumor,meningioma_tumor,glioma_tumor.The explored models have two main parts in their structures, the convolutional part and the classifier part. The convolutional part extracts the inputted image's features and the classifier part classifies these features into one of the intended classes.

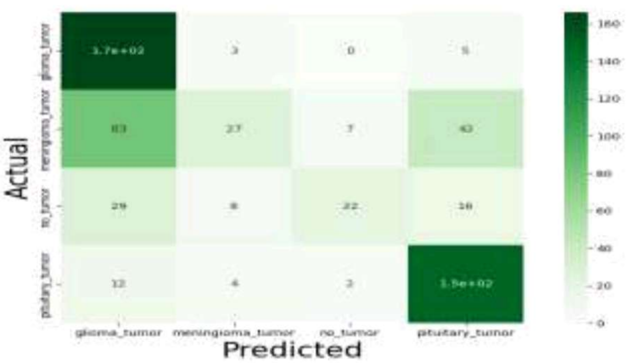


Figure 6. Confusion Matrix

Since "Brain Tumor" has four classes, we must modify the classifier component of these models. Max-pooling layers help speed up diagnosis of MRI images since they reduce the output size of the convolutional layer. However, some MRI picture features may no longer be present as a result of these layers. Confusion matrix shows the actual and predicted outcomes of the input dataset.

V.CONCLUSION

A brain tumour is currently thought to be one of the most susceptible life-threatening illnesses. The inner portion of the human brain, a brain tumor, is surrounded by abnormal cells that have gathered into a cluster. In order to diagnose the tumour accurately and effectively, the patients are required for segmenting and finding the tumour. In order to detect glioma, meningioma, and pituitary brain diseases, a deep convolution neural network architecture is suggested with the goal of achieving high classification accuracy quickly. first, a suitable brain tumour dataset for carrying out the training and testing procedure quickly. Second, a three-step pre-processing method was used to clear the MRI images of any distracting factors, denoise them, and improve their contrast. All of the investigated models were favourably and significantly impacted by this method. Third, as part of a training plan, we train our model from scratch on the desired patterns. Fourth, we employed our model to quickly and accurately classify the MRI images based on their features. We test the suggested model using a dataset containing 2870 MRI pictures. The precision of the suggested model was 99%. In actual use, the suggested model can be viewed as an automated computer-aided detector instrument to accurately and promptly identify brain abnormalities in MRI images.

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