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CNN based approach for detection of brain tumor using MRI scans

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Abstract - Nowadays, manually examining the enormous volume of MRI (magnetic resonance imaging) images and identifying a brain tumour is an extremely time-consuming and imprecise task. It might have an impact on the patient's appropriate medical care. Again, because there are so many image datasets involved, it can take a very long time. The segmentation of tumour locations becomes challenging due to the apparent similarities between brain tumour cells and normal tissue. In this study, we presented a method for segmenting brain tumours from 2D MRIs using a convolutional neural network, which is then followed by conventional classifiers and deep learning techniques. To properly train the model, we have collected a wide range of MRI pictures with variable tumour sizes, locations, forms, and image intensities. To further validate our work, we used SVM classifier and additional activation algorithms (such as softmax, RMSProp, sigmoid, etc.). We use TensorFlow and Keras to build our suggested solution because Python is an effective programming language for quick work. The accuracy of the brain tumour detection in MRI images made possible by our CNN-based model would greatly speed up the pace of treatment.

1. Introduction -

Medical imaging describes several non-invasive technologies for examining the inside of the body [1]. Medical imaging is primarily used in the human body for therapeutic and diagnostic purposes. So, it has a big impact on how well people are treated and how healthy they are. The success of image processing at a higher level is determined by the picture segmentation process, which is a vital and integral phase [2]. In this instance, our primary attention has been on segmenting the brain tumour from the MRI scans. It makes it easier for medical personnel to locate the tumour in the brain. Medical image processing includes the use of 3D images of the physical body acquired most frequently through computed tomography

(CT) or magnetic resonance imaging (MRI) scanners for research, pathology diagnosis, and to guide medical treatments like surgical planning. Radiologists, engineers, and physicians use medical image processing to thoroughly grasp the anatomy of either individual patients or population groupings. The possibility for a more thorough understanding, as an example of interactions between patient anatomy and medical devices, is provided by measurement, statistical analysis, and the development of simulation models that contain genuine anatomical geometries.

The term "tumour" is a synonym for "neoplasm," which is a proliferation of cells that is abnormal. A tumour and cancer are very distinct from one another [3].

1.1. Classification of tumour

There are three basic types of tumours: 1) Benign; 2) PreMalignant; 3) Malignant (cancer can only be malignant)

1.1.1. Benign tumour

Not every benign tumour is malignant or cancerous. It might not spread to other parts of the body or infect nearby tissue the way cancer can. The prognosis for benign tumoursis typically not alarming, but it might be alarming if it presses on essential organs like blood arteries or nerves.

1.1.2. Pre-Malignant tumour

The cells in these tumours are not malignant. They must, however, have the capacity to develop into cancer. The cells will develop and spread to form different body parts.

1.1.3. Malignant tumour

Malignancy (from the Greek,, "badness" and, "fire") Cancerous tumours are malignant tumours. When cells proliferate uncontrollably, they emerge. The disease will become dangerous if the cells continue to develop and unfold. Malignant tumours will spread fast to different parts of the body using a process called metastasis. A latest research [5] in the year 2021 says that in United States among 24530 adults (13840 men & 10690 Women) will be identified with cancerous tumours of brain and in the spinal cord. A person's probability of developing this type of brain tumour in their lifespan is less than 1%. It causes 85% to 90% of all primary central nervous system (CNS) tumours. Aside from adult primary brain tumours, this year will also see the diagnosis of 3,460 children under the age of 15 with a brain or CNS tumour. Cancer of the brain and other nerve systems ranks as the tenth most common cause of death for both sexes. The estimated number of persons who will pass away in 2021 from primary malignant brain and CNS tumours is 18,600 (10,500 males & 8,100 women).To advance medical imaging research, it is crucial to increase the accuracy of previously suggested methodologies. Our 99.74% accurate CNN-based method is proposed in our paper to assist medical representatives in their treatment tasks without manually interpreting the MRI images, hence enhancing the treatment pace.

2. Methods for brain tumour segmentation

The three categories of brain tumour segmentation techniques are as follows. Methods include manual, semi-automatic, and fully automatic. The amount of user engagement needed will help us decide [6].

2.1. Manual segmentation methods

A medical specialist is required to use the many data seen by the MRI images in conjunction with anatomical and physiological knowledge acquired through education and practice. The medical expert must meticulously crop the tumour regions

by hand after carefully going over numerous slices of photos one at a time and assessing the brain tumour. It takes a lot of time because manual segmentation relies on the doctor and has significant intra- and inter-rater variability [7]. Nonetheless, this is frequently used to implement the outcomes of fully automatic and semi-automatic approaches.

2.2. Semi-automatic segmentation methods

There are three basic goals for which it requires the user's response: initialization, intervention or feedback response, and evaluation [8]. A region of interest (ROI) is primarily defined during initialization in order to constrain the estimated tumour area for the automatic algorithm to analyze. To fit the input photos, pre-processing procedure parameters might also be balanced. Automated algorithms can be guided towards a required outcome throughout the process by receiving feedback in addition to initialization. The adjustments made in response are likewise provided by this method. Once more, if the user is not pleased with the results, they can estimate them again or repeat the process. The "Tumour Cut" approach was proposed by Hamamci et al. [9]. This technique involved using the algorithm to each MRI modality separately (e.g. T1, T2, T1-Gd and FLAIR). The ultimate tumour volume is then calculated by combining the results. A modern semi-automatic technique used with a fresh categorization strategy [10]. By training and classifying exclusively inside the same brain, this approach segments a brain tumour by converting the segmentation problem into a classification problem. For brain tumour segmentation, a machine learning classification technique typically requires a large number of brain MRI scan pictures (with checked responses) from various instances to train. This result is required to handle noise and intensity bias correction. Nevertheless, in this method, the user initializes the process by selecting a subset of voxels from a single example that are associated with each tissue type. A support vector machine (SVM) is trained to classify all the voxels in an image to the appropriate tissue type using the intensity values and spatial coordinates extracted from these subsets of voxels as features. Semi-automatic brain tumour segmentation methods can maintain effective results while taking less time than manual methods, but they are still subject to intra- and inter-rater user variability. Hence, completely automatic techniques are the main focus of current research on brain tumour segmentation.

2.3. Absolute automatic segmentation methods

This method does not require user interaction. Most crucially, the segmentation issue is resolved by combining artificial intelligence and background information.

2.3.1. Challenges

A difficult and significant issue is the automatic segmentation of gliomas, a form of tumour that can develop in the brain and spinal cord. Clinical scans or artificial databases used to generate brain tumour MRI data are inherently complex [11]. The MRI equipment and acquisition techniques can change dramatically from scan to scan, imposing intensity biases and other variances for each unique section of the dataset's images. Its intricacy is even increased by the necessity to segregate cancer sub-regions using multiple modalities.

2.3.2. BRATS dataset

The Multimodal Brain Tumour Image Segmentation Benchmark is referred to as BRATS. It is challenging to evaluate the effectiveness of several state-of-the-art technologies for segmenting brain tumour images. Additionally, with the implementation of a widely used benchmark for automatic brain tumour segmentation, the BRATS benchmark [12], it is now possible to objectively compare different glioma segmentation algorithms using this shared dataset. The most recent version (2020) of the BRATS training dataset contains 369 multi-modality MRI scans, of which 293 were obtained from patients with glioblastoma (GBM/HGG) and 76 from lower grade glioma (LGG), together with their ground truth segmentations for evaluation [13]. Only the online assessment tool makes it possible to assess the testing data. The programme primarily displays outcomes as the widely recognized Dice Score, Sensitivity (true positive rate) and Specificity (true negative rate) for the three primary tumour parts: total tumour (all tumour components), core tumour (all tumour components minus edoema), and active tumour (only active cells). Dice results are typically used as performance indicators. The segmented tumour area P1 for each tumour region is represented by the suggested approach, and the real tumour area T1 is represented by the ground truth. The online tool then determines the dice score for each zone as

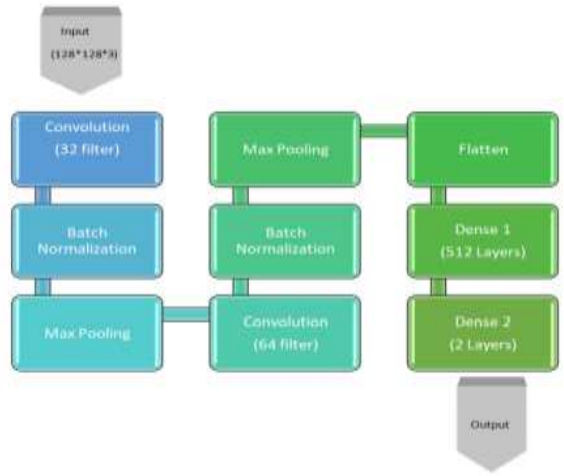

Fig. 1. Proposed methodology for tumour detection using 9-Layer Convolutional Neural Network.

3. Proposed methodology

Convolutional Neural Network is an organized technique used in the processing of medical images. A convolutional neural network (CNN) is a form of artificial neural network that specializes in learning technique component knowledge and is used for image recognition. CNN is an effective image processing and computing technique that uses deep learning to carry out both generative and descriptive tasks. It typically makes use of machine vision, which has the ability to recognize images and videos, as well as recommender systems and linguistic communication processes (NLP). A neural network might be a system of hardware and computer code that mimics how neurons in the human brain function. Artificial neural networks are not the best choice for processing images. A CNN employs a method like a multilayer view-point that has been created for less process requirements. A system that is significantly more effective and simpler to train data for both language communication and image processing results from the elimination of restrictions and

improvement in image processing potency. The core CNN model has been modified, and a significantly improved version has been projected. With our nine-layer CNN model, there are fourteen phases in addition to the hidden layers that provide us the best possible outcome for detecting the tumour. The intended methodology is depicted in Fig. 1 along with a brief narrative. In the method we've suggested, we've used a wide range of photographs as input and changed every one of them to the uniform dimensions of 128*128*3. We tend to construct a convolutional kernel with a convoluted input layer that employs 32 convolutional filters, each of size 2*2, with the assistance of 3 channel tensors. ReLU is frequently utilized by us because to its activation feature. The corrected linear activation function, or ReLU, is a piecewise linear function that, if the input is positive, outputs the input directly; if not, it outputs zero. Then, in 2015, we used the batch normalization method suggested by Sergey Ioffe et al. If the input is positive, the corrected linear activation function, or ReLU, will output the input directly; if the input is negative, it will output zero. Next, we used the batch normalization method suggested by Sergey Ioffe et al. [14] in 2015. Batch normalization [15] (also known as the batch norm) is a method that, in addition to producing neural networks more quickly, also increases stability by normalizing the inputs to the layers by re-centering and rescaling. That helped us quickly develop our algorithm. See Fig. 2. The pooling operation then entails applying a 2D filter to each channel of the feature map and summing the features that are present within the filter's coverage area. The output dimensions for a feature map with dimensions after a pooling layer $n_h*n_w*n_c$ is $(n_h - f + 1) /s * (n_w - f + 1) /s * n_c$

where,

->n_h - height of feature map

->n_w - width of feature map

->n_c - no. of channels in the feature map

-> f - size of filter -> s - stride length

We have used a 2*2 Max pooling procedure [16] in this case, which chooses the largest element from the feature map's range that the filter can cover. Thus, a feature map comprising the most crucial features of the prior feature map would be the output following the max-pooling layer. view figure 3.

After this step, we once more utilized 64 convolutional filters with batch normalising and max-pooling approaches before flattening. We suggested two dense layers, the first of which has 512 hidden levels and the second of which has the final two. Since softmax provides greater accuracy than other activation functions, we used it as the final layer's activation function. Once more, we used the "categorical crossentropy" loss function and the RMSProp optimizer. RMSProp is an extension of gradient descent and an Adaptive Gradient Algorithm version of gradient descent that uses a decaying average of partial gradients in the adaptation of the step size for each parameter. The proposed CNN model's operational flow is depicted in Fig. 4.

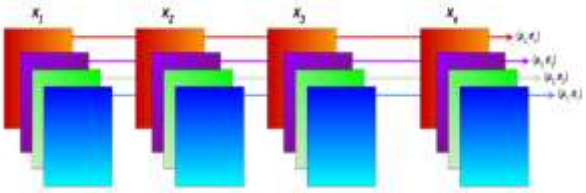

Fig. 2. Batch normalization.

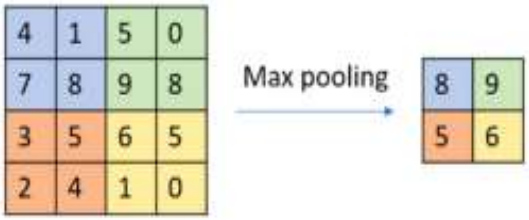

Fig. 3. 2*2 Maxpooling operation.

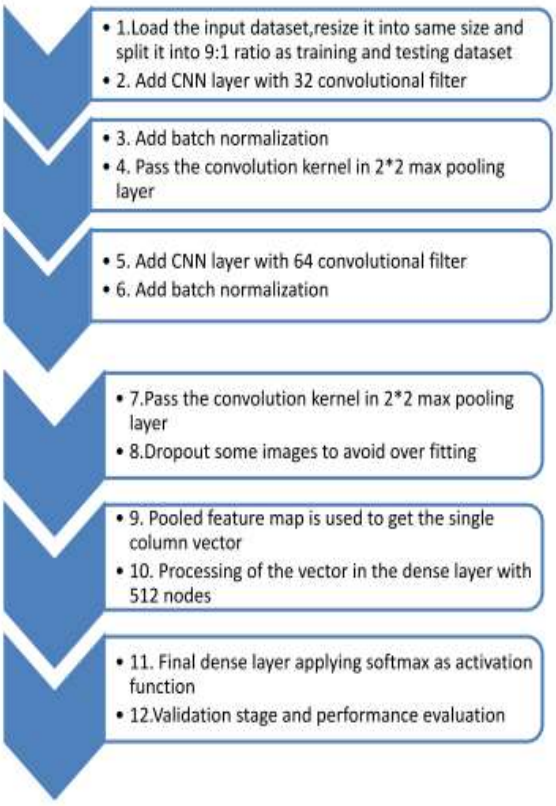

Fig. 4. Working flow of the proposed CNN model.

Table 1

Comparison of different models.

Final Layer Activation Method	Optimizer	Accuracy (%)	Testing Accuracy (%)	Evaluation of the Model (%)
SVM	N/A	15.17	20.83	24.17
Sigmoid	RMSProp	97.63	58.33	68.72
Softmax	AdaMax	98.10	75	82.40
Softmax	RMSProp	**99.74**	93.78	97.71

4. Experimental results

4.1. Experimental dataset

For our experiment, we used the BraTS dataset for 2020. We captured a total of 2892 pictures of various tumour kinds, including T1, T2, and FLAIR. This dataset consists of two classes: class 1 refers to photos of tumours, and class 0 refers to images without tumours. In Figs. 5 and 6, respectively, some tumour datasets and non-tumor datasets from our input photos are displayed.

4.2. Results and discussion

Tables 1 and 2 demonstrate the outcomes of our experiments using various CNN activation functions, optimizers, and models. The AdaMax algorithm, which is an extension of the Adaptive Movement Estimation (Adam) Optimization technique, was the first thing we tested. We found accuracy of 99.74% utilizing softmax in the final layer with RMSProp as optimizer, which is acquired by using 2473 number of training photos, 273 number of testing images, and a 9:1 splitting ratio. This is an addition of the Gradient Descent Optimization approach, more widely. To avoid overfitting, we removed a small percentage of these images (around 5%) from the entire dataset of 2892 images.

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Fig. 7 displays the results of the suggested strategy using 11 different epoch numbers. The training and validation accuracy in Fig. 8 is displayed in relation to the number of epochs, and Fig. 9 displays the equivalent loss.

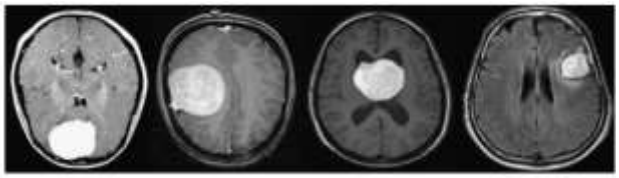

Fig. 5. Images with tumour

Fig. 6. Images with non-tumours

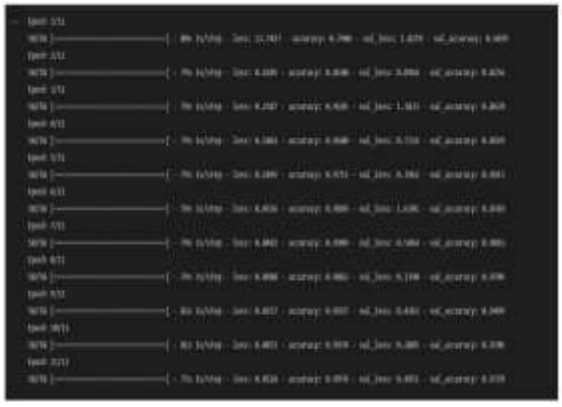

Fig. 7. Final output of our proposed method

Table 2

Performance of the proposed CNN model.

No	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	2199	543	8:2	99.73
2	2473	273	9:1	99.74

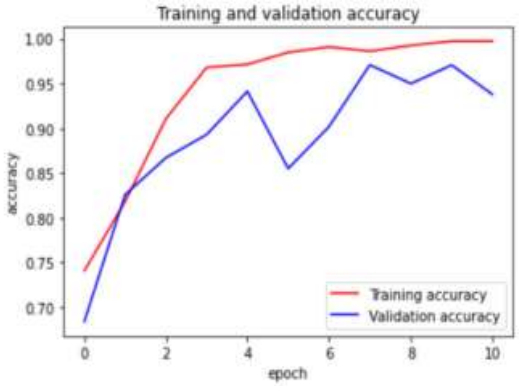

Fig. 8. Training and validation accuracy.

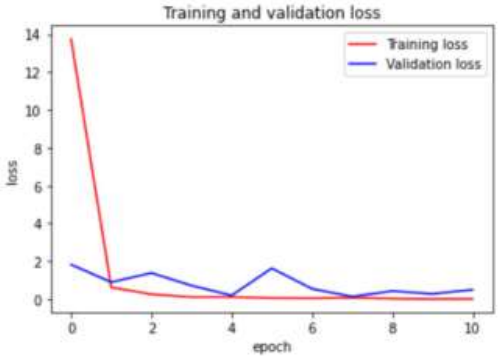

Fig. 9. Training and validation loss.

As shown in Table 3, we achieved 99.74% accuracy in this suggested model, which is greater than the state-of-the-art values reported by Seetha et al. [17] and Tonmoy Hossain et al. [18].

Table 3

Performance comparison.

Methodology	Accuracy (%)
Seetha et al. [17]	97.50
Tonmoy Hossain et al. [18]	97.87
Proposed CNN model	**99.74**

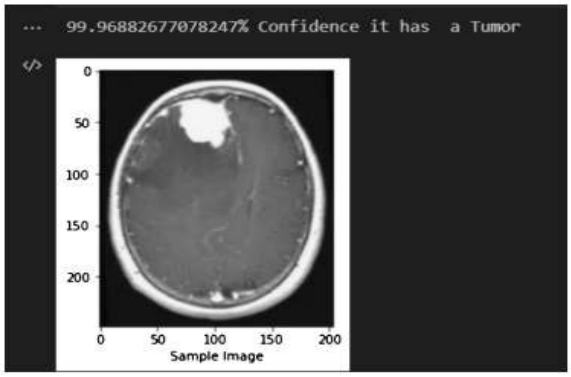

Fig. 10. Prediction by our proposed model

5. Conclusion

The most common applications of MRI are for tumour segmentation and classification. We chose to increase the accuracy of convolutional neural networks (CNN) despite the fact that they have the advantage of automatically learning representative complex characteristics for both healthy brain tissues and cancer tissues from the multi-modal MRI images. The first time we tried to use SVM on CNN, the accuracy was only 20.83%. Then we experimented with various parameters. We updated the optimizer to AdaMax and the final layer parameter to softmax. The accuracy was then 98.10%. However, we still needed more, so we changed the optimizer to RMSProp, and in the end, we were able to increase the output accuracy to 99.74%. We ultimately obtained our final result by employing 2473 numbers of photos as training data and 273 images for testing in a 9:1 ratio with an 11-epoch approach. Our model uses a 14-stage, 9-layer CNN model. In order to avoid overfitting, we also eliminated several photos.

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