Brain Tumor Detection Using Convolutional Neural Network

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***Abstract*—Brain Tumor segmentation is one of the most crucial and arduous tasks in the terrain of medical image processing as a human-assisted manual classification can result in inaccurate prediction and diagnosis. Moreover, it is an aggravating task when there is a large amount of data present to be assisted. Brain tumors have high diversity in appearance and there is a similarity between tumor and normal tissues and thus the extraction of tumor regions from images becomes unyielding.This paper proposes to identify pituitary brain tumors. We used publicly available dataset that include 253 MRI images after augmentation we have got 2056 MRI images.To build our models, we applied 8 layered - convolution neural network (CNN) with a single convolution layer with 32 filters which is implemented using Keras and Tensorflow because it yields to a better performance than the traditional ones. In our work, CNN gained an accuracy of 88.7 percent on testing set and 91 percentage acccuracy on validation set.**

***Index Terms*—CNN,MedicalImage,Augmentation,Accuracy.**

I. Introduction

MEdical imaging refers to a number of techniques that can be used as non-invasive methods of looking inside the body [1].Medical imaging, which uses a variety of imaging modalities and procedures to picture the human body for diagnostic and therapeutic purposes, is crucial to decision-making when it comes to improving people's health.

According to [3],The five-year survival rate for individuals with brain cancer is 34 percentage for men and 36 percentage for women. Brain and other nervous system cancer is the tenth largest cause of death. Along with this, the World Health Organization (WHO) reports that 120,000 people have passed away from brain tumours in the past few years, affecting about 400,000 people globally.[4]. Furthermore, it has been predicted that the United States will diagnose 86,970 new cases of primary malignant and non-malignant brain tumours as well as other Central Nervous System (CNS) tumours in 2019 [5].
When abnormal cells develop within the brain, a brain tumour results [6]. Tumours can be classified as benign or cancerous. Brain tumours that are cancerous begin in the brain, grow quickly, and then aggressively spread to the surrounding tissues.It has the potential to spread to other regions of the brain and impact the central nervous system. Primary tumours, which originate inside the brain, and secondary tumours, which have spread from outside the brain, are the two categories into which malignant tumours fall.A harmless brain tumour, on the other hand, is a mass of cells that develops in the brain more slowly.
Early detection of brain tumours can therefore be extremely helpful in increasing treatment options and achieving a higher chance of survival. nevertheless, because a lot of MRI images are created during routine medical procedures, manually separating tumours or tumours is a difficult, time-consuming task. Magnetic Resonance Imaging, or MRI for short, is most commonly used to detect lesions in the brain or tumours. Given that brain tumour segmentation from MRI typically requires a significant amount of data, it is one of the most important tasks in the processing of medical images. Furthermore, soft tissue boundaries may cause the tumours to be ill-defined. Therefore, accurately separate tumours from the human brain is a very big task.
In this paper, we presented an effective and clever approach based on both conventional classifiers and convolutional neural networks that helps in the identification of brain tumours without the need for human intervention.

II. LITERATURE REVIEW

Brain tumor detection and classification play a pivotal role in modern medical diagnostics, enabling timely and accurate identification of abnormalities within the brain. As technological advancements have transformed the landscape of medical imaging, researchers have increasingly turned to sophisticated algorithms, such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs), to enhance the precision of detection and classification processes.

Over the years, several studies, including those by Devkota et al. (2017), Song et al. (2016), Dina et al. (2012), and Zahra et al. (2018), have contributed valuable insights into these methodologies. However, with the rapidly evolving field of medical imaging and machine learning, there exists a need to address research gaps and potential errors to ensure the robustness and reliability of these techniques. This literature review examines key studies, methodologies, results, research gaps, and potential errors in brain tumor detection and classification, offering a comprehensive overview of the current state of research and identifying avenues for future exploration.

Study	Objective	Methodology	Results	Research Gap
Dina et al. 2012	Brain tumor detection	Decision tree	Attained 95.2% accuracy	Limited discussion on data variability
Song et al. 2016	Adaptive brain tumor detection	Unsupervised Support Vector Machine	Proposed an adaptive approach	Lack of comparison with supervised methods
Devkota et al. 2017	Brain tumor segmentation on MRI images	Convolutional Neural Network algorithm	Achieved 90% accuracy	Limited exploration of other segmentation techniques
Zahra et al. 2018	Brain tumor classification	Artificial Neural Network algorithm	Successfully classified tumor types	Lack of comparison with other classification algorithms
Tonmoy Hossain et al. (2019)	Brain tumor detection using CNN	CNN algorithms	Conference paper, specific results not provided	Limited information on dataset characteristics
Md. Saikat Islam Khan et al. (2022)	Accurate brain tumor detection using deep CNN	Deep Convolutional Neural Network	Published online Aug 27, 2022	Lack of real-time evaluation metrics
Soheila Saeedi et al. (2023)	MRI-based brain tumor detection	Convolutional deep learning methods	Published in BMC Medical Informatics and Decision Making, January 2023	Lack of discussion on model interpretability
June 2023 Study on TCGA-LGG and TCIA Dataset	Brain Tumor Detection and Classification	Fine-Tuned CNN with ResNet50 and U-Net Model	Published in June 2023	Limited explanation of model fine-tuning process

Fig. 1. Literature Review

III. PROPOSED METHODOLOGY

The paper aims to tackle the difficult problem of identifying brain tumours in medical images, with a particular focus on pituitary brain tumour detection. Inaccuracies can arise from manual classification by human experts, and the complexity increases with the amount of data involved. Because brain tumours have a variety of inherent appearances and because normal tissues and tumours are similar, an automated and reliable classification model must be created. The goal of this work is to provide a method for precisely identifying and differentiating pituitary brain tumours from magnetic resonance imaging (MRI) data using a 8-layer convolutional neural network (CNN) with a single convolution layer with 32 filters of size 7x7 and stride 1,1.

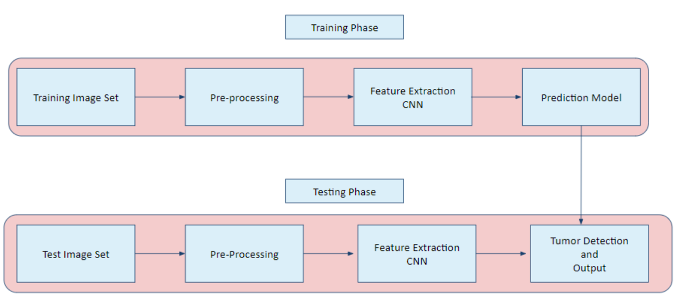


Fig. 2. Proposed Model

A. *Proposed Methodology Using CNN*

Convolutional Neural Network is broadly used in the field of Medical image processing. Over the years lots of researchers tried to build a model which can detect the tumor more efficiently. We tried to come up with an exemplary which can accurately classify the tumor from 2D Brain MRI images. A fully-connected neural network can detect the tumor, but because of parameter sharing and sparsity of connection, we adopted CNN for our model.

A eight-layered convolutional neural network is introduced and implemented for tumor detection with stride of (1,1). The aggregated model consisting of seven stages including the hidden layers provides us with the most prominent result for the apprehension of the tumor. Using convolutional layer as the beginner layer, an input shape of the MRI images is generated which is 240*240*3 converting all the images into a homogeneous dimension. After accumulating all the images in the same aspect, we created a convolutional kernel that is convoluted with the input layer—administering with 32 convolutional filters. ReLU is used as an activation function.

In this ConvNet architecture, progressively shorten the spatial size of the depiction for diminishing the chunk of parameters and computational time of the network. Working on the Brain MRI image can also cost the contamination of the overfitting and for this Max Pooling layer perfectly works for this perception. For spatial data which substantiate with our input image, we use MaxPooling2D for the model 2 times with a pool size of (4,4) and finally we obtain the dimension 14*14*32. The flatten layer transforms the 3D tensor into a 1D vector, which is required before passing the data to a fully connected layer and size becomes 6272. One connected layers is employed Dense-1 and representes the dense layer. The dense function is applied in Keras for the processing of the Neural Network, and the obtained vector is work as an input for this layer.

ReLU is used as the activation function because of showing better convergence performance.In the dense layer we used sigmoid function as activation function because we need to lower the uses of computing resources so that a more significant amount assuages the execution time.Though there is a chance of hampering the learning in deep networks for using of the sigmoid as the activation function, we scale the sigmoid function, and the number of the nodes is much lesser and easy to handle for this deep network. In a summary, Fig. 2 shown the working flow of the proposed CNN model.

Using Adam optimizer and binary cross-entropy as a loss function, we compiled the model and find the accuracy of detecting the tumor.An algorithm is depicted in Fig. 3 where we evaluated the performance of the model.

IV. EXPERIMENTAL ANALYSIS

The proposed models are implemented in TensorFlow, with Keras in Python. The implementation was performed on Google Colab which provides free online cloud service along with 15 GB of free space in google drive.

A. *Experimental Dataset*

For Performance Evaluation of our proposed model, we used the dataset contains 2 folders yes and no and total 253

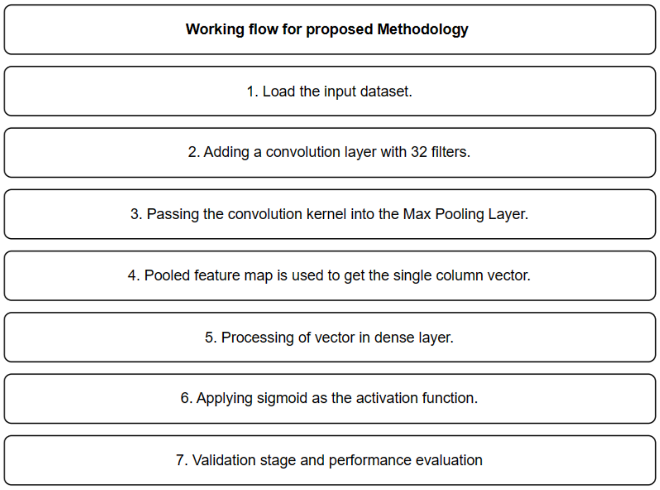


Fig. 3. Working Flow

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig. 4. Algorithm of the performance evaluation

MRI image folder yes contains 155 Brain MRI images that are tumorous folder no contains 98 Brain MRI images that are non-tumorous.Since this is a small dataset, I used data augmentation in order to create more images.Also, we could solve the data imbalance issue.

Since 61 percent of the data (155 images) are tumorous. And, 39 percent of the data (98 images) are non-tumorous.So, in order to balance the data we can generate 9 new images for every image that belongs to no class and 6 images for every image that belongs the yes class.

For traditional machine learning classifiers, we obtained the superlative result splitting the dataset by 70 percent for training 15 percent for testing and 15 persent for validation.

B. Data Preparation and Preprocessing

In order to crop the part that contains only the brain of the image, we have used a cropping technique to find the extreme top, bottom, left and right points of the brain.Resize the image (because the images in the dataset come in different sizes we want all of our images to be (240, 240, 3) to feed it as an input to the neural network.

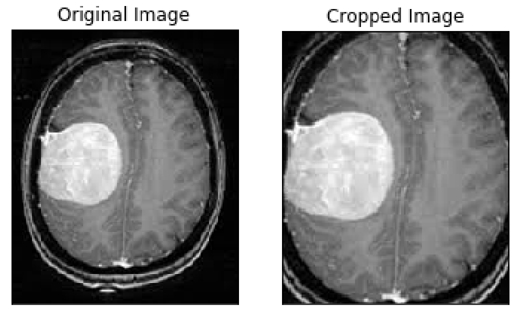
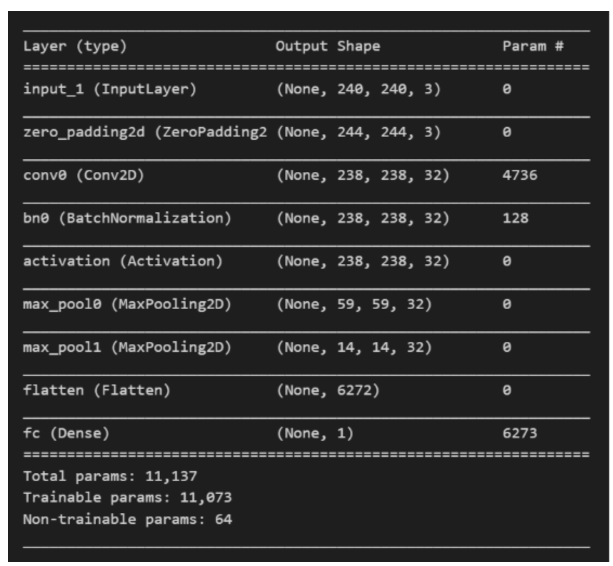


Fig. 5. Comparison between Original image and cropped image

Apply normalization because we want pixel values to be scaled to the range 0-1. Then combine the dataset with the augmented dataset and finally plot the sample images.

C. Build the CNN Model

The eight-layer proposed methodology gives us the commendable result for the detection of the tumor. Convolution, Max Pooling, Flatten, and one dense layers is the proposed eight layered CNN model. Data augmentation had been done before fitting the model as CNN is translation invariance.Fig 5 represent the summary of our model.We evaluate the performance based on splitting the dataset into 70:15:15. We accomplish 91 percent of accuracy on validation set and 89 percent for test set. Now we train the our model having a batch size of 32 upto 24 epochs.



Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 240, 240, 3)	0
zero_padding2d (ZeroPadding2	(None, 244, 244, 3)	0
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. 6. Model summary

Fig. 6 depicts the training loss and validation loss of our model.Fig 7 depicts the training accuracy and validation accuracy It was calculated by the Keras callbacks function. Operating with the different number of epochs we observed that on 23rd iteration model is having a validation accuracy of 91 persent which is considered best model for testing.

Fig. 7. Loss of the proposed CNN model.

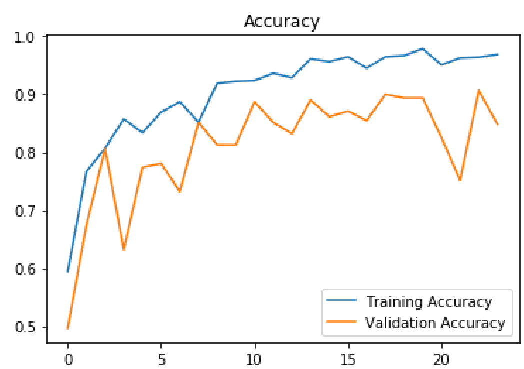


Fig. 8. Accuracy of the proposed CNN model

V. RESULTS

Finally we test our best model on the testing dataset.And we calculate the f1 score and accuracy of the model.

Now, the model detects brain tumor with: 88.7 percent accuracy on the test set. 0.88 percent f1 score on the test set. These resutls are very good considering that the data is balanced.

Performance Table:

	Validation set	Test set
Accuracy	91%	89%
F1 score	0.91	0.88

Fig. 9. Performance table

VI. CONCLUSION

In conclusion, this study successfully proposed a 8-layered convolutional neural network (CNN) approach for the pituitary brain tumors in MRI images. The utilization of this advanced deep learning model yielded promising results, with an accuracy of 89 percentage on the testing set and 91 percentage on the validation set. The significance of this research lies in its potential to overcome the challenges associated with manual classification, especially in the context of a large and diverse dataset. The CNN architecture demonstrated its ability to discern intricate patterns and features, making it a valuable tool in the accurate identification of pituitary brain tumors. The comparison with traditional approaches further emphasized the superior performance of the proposed CNN model.

VII. FUTURE SCOPE

The future scope outlines potential directions for further research and development in the field of automated pituitary brain tumor, with a focus on refining existing methodologies and exploring new avenues to enhance accuracy, efficiency, and clinical impact. Several potential directions for future research include:

- Advanced Model Architectures: Explore deeper CNN architectures or incorporate attention mechanisms for improved feature capture. Investigate transfer learning and domain adaptation for better convergence.
- Data Augmentation and Synthesis: Implement advanced data augmentation techniques and synthetic data generation, like GANs, to address data scarcity and enhance model robustness.
- Clinical Decision Support Systems (CDSS): Extend the model to serve as a CDSS, providing additional insights such as tumor classification or treatment response prediction for informed decision-making.
- Real-Time Image Processing: Develop models for real-time segmentation, particularly in intraoperative settings, to aid surgeons and enable immediate decision-making.
- Integration with Electronic Health Records (EHR): Explore integration with EHR for a seamless flow of information, connecting model predictions with patient medical history for a holistic approach to care.

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