Brain tumor image classification

1. Introduction

In medical image processing ,due to their variations in sizes and texture in the photos, classification task of brain tumor is difficult. However, clinicians typically perform manual tumor detection on MRI images. In our work, a technique was developed that could help physicians identify brain tumors using MRI images[1].The likelihood of survival can be increased if a tumor is correctly diagnosed at an early stage.The difficulties that practically all digital photographs have, such as illumination issues, detecting and classify the type of brain tumors more challenging for any algorithm to accurately forecast from the MRI photos when tumor[2] ,non-tumor images have overlapping image intensities[3].We applied the picture pre-processing methods that have been chosen for training, the study also addresses other methods and their effects on the dataset. On a dataset with various tumor sizes, forms, textures, and locations with experiments. To classify the type of tumor, CNN with transfer learning is used[6]. In our work, it outperformed in classifying brain tumors, with accuracy of 90% on testing samples.

2. Related Work

In this investigation, the proposed method has the highest accuracy compared to other current methods. Brain tumors that are segmented to determine tumor area and area percentage are covered by Wulandari et al. [2]. A thresholding technique is needed for the tumor segmentation procedure, and the process is repeated until the greatest area is found. The watershed method is utilised to designate the brain and its surrounding regions, and the cropping method is then applied to remove the skull. This system's average inaccuracy in estimating the tumor area is 10%. Gopika and Rajasree [4] proposed a hybrid method to identify brain cancers in MRI images by combining texture and grayscale data.

Four steps are needed for hybrid focusing technology: filtering, feature extraction, feature reduction, and classification. Diffusion support vector machine (FSVM) was utilised in this study to categorise the tumor and determine whether it was benign or malignant[5]. The accuracy of the suggested procedure is 85% accurate.

An intelligent classification method was put forth by Nandpuru et al. [3] to distinguish between normal and pathological MRI brain pictures. Utilizing grayscale, symmetry, and texture features, MRI features are extracted. For classifying brain images, the Support Vector Machine (SVM) classification algorithm is suggested. To the SVM testing step, this study used linear and other kernels In this study, SVM using a quadratic kernel had the highest accuracy rate 87.03%[6].

The proposed methodology tries to distinguish between healthy brain tissue and brain tumor with accuracy rate 90%.The results show that with our AI model, when applied to the right training data set, can distinguish between abnormal and normal tumor regions and correctly classify them as benign tumors, pituitary tumors, or healthy brains.

3. Materials and Experimental Evaluation

3.1 Datset

The dataset consists of 789 images with jpeg format. In our initial prospective model, machine learning algorithms were used to segment and detect brain tumors with three classes, and a comparison of the classifiers for our model was established. Those are glioma tumor ,pituitary tumor, no tumor. Their images are 260,260,269 respectively.In our model 80 % dataset is used for training and remaining 20% is used for testing and validation .

3.2 Methodology

In the field of medical image processing, convolutional neural networks are frequently employed[7]. Many scientists have worked on developing a model that can more effectively detect tumors throughout the years[8]. We made an effort to develop an example that can correctly categorise the tumor from 2D Brain MRI images.

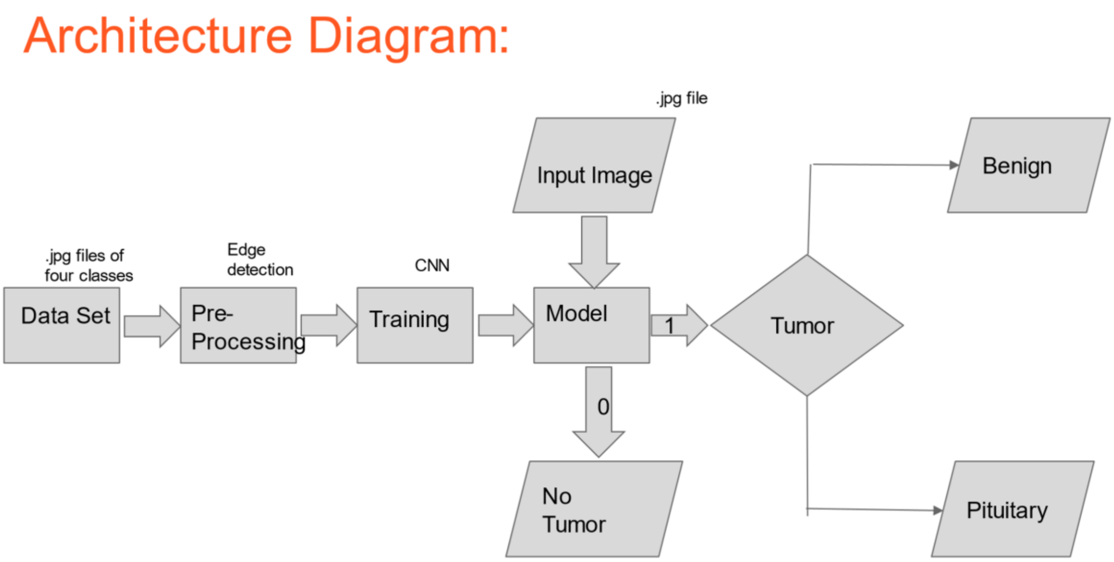

Figure 1. Proposed Methodology for tumor detection

Although a fully-connected neural network can detect the tumor, we chose CNN for our model in figure 1 due to parameter sharing and connection sparsity.

The parameters used in our model are Epochs, basic learning rate, optimiser ,batch size, Number of classes are the parameters used in our proposed model. The results of multiline plot is shown in figure 2.

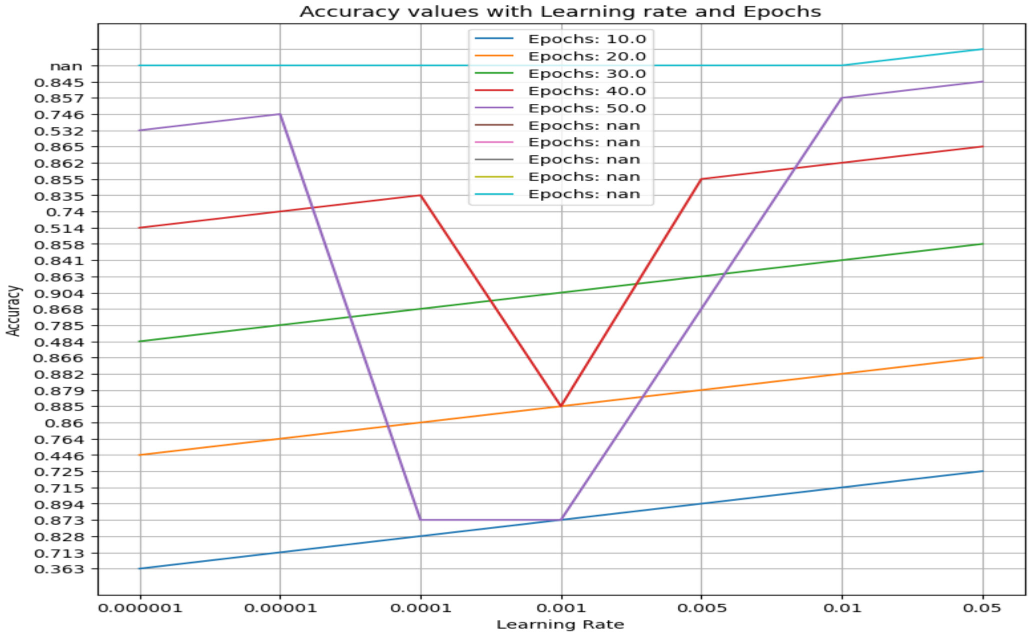

Figure 2 :Multiline plot

3.3 Results

The confusion matrix of AI model as shown in figure 3

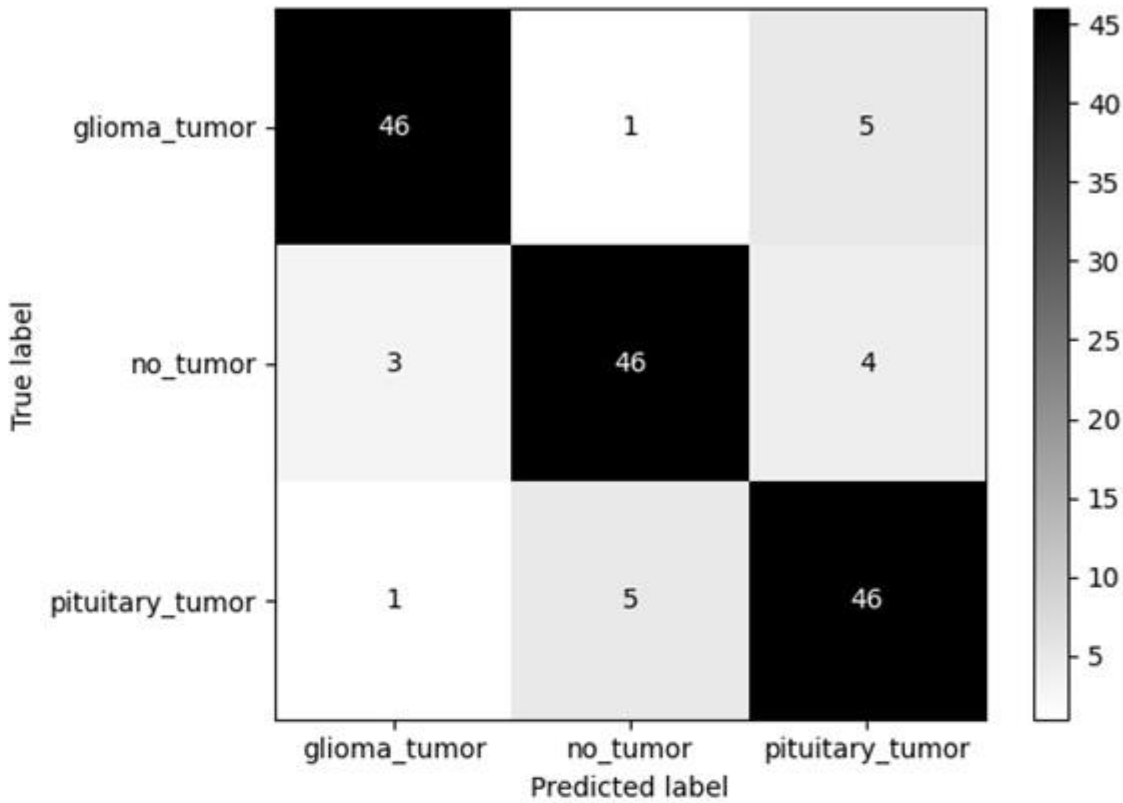

Figure 3:Confusion matrix

The proposal model tries to distinguish between no tumor and brain tumor with accuracy rate 90%.The classification report is shown in figure 4.

Classification Report :

	precision	recall	f1-score	support
0	0.92	0.90	0.91	52
1	0.90	0.89	0.90	53
2	0.89	0.90	0.88	52
accuracy			0.90	157
macro avg	0.90	0.90	0.90	157
weighted avg	0.90	0.90	0.90	157

Figure 4:Classification report

3.4 Discussion

Authors/Year	**Performance**
Vani et al.[4]	81.47%
Citak et al. [8]	83.00%
Mohsen et al.[9]	87.94%
Proposed model	90%

Table 1

The suggested models for extracting deep learning-based features are helpful and discriminating features to categorise the various types of tumor in a complex feature's assessment of various tumor types.According to suggested tumor categorization models, the glioma and pituitary tumor classes recovered more accurately .Table 1 also compares various methods currently in use.The categorization of brain tumors using the proposed model's. The parameters used in our model are epochs, basic learning rate, optimiser ,batch size, Number of classes are the parameters used in our proposed model.

In summary, MobileNetV2 is a highly efficient and accurate CNN architecture that is specifically designed for mobile and embedded vision applications. Its inverted residual blocks, depthwise separable convolutions, and pointwise convolutions make it a popular choice for developers working on resource-constrained devices.

4. Future Work

For brain tumors classification, we will later research and put into practise ways for fine-tuning pre-trained models that have been trained using more layers and scratch-based models with data augmentation techniques. We'll also look into ensemble approaches that use features that were developed, improved, or created from scratch. Future scope is on various datasets of 2D and 3D MRI images for the classification of brain tumors with high rate accuracy.

5. Conclusion

In conclusion, the feature retrieval in the image and the classification process are significantly impacted by better segmentation results. classify the three different types of brain tumors classes: gliomas tumors, pituitary tumors and no tumor using pre-trained MobileNetV2 model methods. The suggested method generated 90% testing accuracy on test samples and displayed the highest performance in the classification of brain tumors.

6.Reference

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