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Brain Tumour Detection on MRI images using Artificial Intelligence

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Abstract - Tumours cause the second most cancer in the world. Cancer endangers many sufferers. Medical professionals require a rapid, automated, efficient, and reliable approach to detect brain tumours. Early detection is key. Early tumour detection may save a patient's life. This application uses image-processing techniques. This technology has saved numerous cancer patients' lives. Uncontrollable cell development causes tumours. Brain tumour cells may eat all the nutrients meant for healthy cells and tissues, causing brain failure. Clinicians utilise MRI pictures of the patient's brain to locate and measure tumours. As a result, detecting the tumour is difficult and time-consuming. Tissue tumours proliferate uncontrollably. Deep Learning architectures like as CNN, NN, and VGG 16 may be used to identify brain tumours (visual geometry group). Effective models reliably estimate if an image has a tumour. If there's a tumour, yes; otherwise, no.

***Key Words*:** Brain tumour, MRI, CNN, VGG-16, detection.

1.INTRODUCTION

Every part of the organism receives sensory information and responds to it through the central nervous system (1–3).

The brain, along with the spinal cord, aids in the spread of this information. The brain stem, the cerebrum, and the cerebellum make up the bulk of the brain's anatomical structure [4]. Normal human brain weight and volume are around 1.2–1.4 K and 1260 cm3 (male brain) and 1130 cm3 (female brain), respectively [5].

There are several functions of the brain's frontal lobe that help in problem-solving, such as motor control and judgements. Body position is controlled by the parietal lobe. The temporal and occipital lobes of the brain are responsible for memory and hearing, respectively. There is a grey layer called the cerebral cortex on the outside of the cerebrum.

2. LITERATURE SURVEY

Automated detection and segmentation of afflicted brain tumour regions is proposed by C. Hemasundara Rao et al, the suggested approach has three stages: 1. Segmentation at the outset 2. Energy function modelling and 3. Energy function optimization. T1 and FLAIR MRI images are mined for their information in order to provide segmentation results that are as accurate as possible. The information from T1 and FLAIR is combined in a probabilistic area using a CRF (Conditional random field)-based framework [4].

New multi-fractal feature extraction and improved AdaBoost classification techniques are recommended by Atiq Islam et al. for the identification and segmentation of brain tumours. The brain tumour tissue texture is retrieved using the MultiFD feature extraction approach. To determine whether or not the brain tissue has been impacted by a tumour, the improved AdaBoost classification algorithms are used. The design has a significant degree of intricacy [1].

CNN is one of the greatest image-analysis tools. CNN predicts by shrinking images without losing necessary information. The same may be done with picture augmentation and ANN and CNN performance analysis. The model is built by trial and error. Future optimization strategies may determine the amount of model layers and filters. For the supplied dataset, CNN is superior at predicting brain tumours.[2]

The use of MRI images for brain tumour diagnosis has been proposed by J. Seetha et al. Time-consuming manual data categorization of tumour vs. non-tumor is a common problem with MRI scans.

Despite the fact that it only measures a limited number of photos with precision quantitative parameters. As a result, it becomes necessary to develop categorization methods that are both automated and trustworthy in order to lower the human fatality rate. A considerable spatial and anatomical discrepancy between adjacent sites of brain tumour may complicate the automated categorization of brain tumours.

This paper presents a method for automatically detecting brain tumours based on CNN classification [3]. Extraction of gray-level co-occurrence matrix (GLCM) characteristics, as well as brain tumour area growth segmentation (Dwt) for reducing complexity while increasing performance are the main goals of N. Varuna Shree and colleagues. After segmentation, morphological filtering is used to remove any noise that may have built up. Tumor site detection using MRI images of the brain is being tested and trained using the probabilistic neural network classifier [4].

Brain tumour auto-diagnosis technique proposed by Othman and Ariffanan in [5]. [6] Probabilistic Neural Networks classify patterns (PNN). UTK data was preprocessed for this study. MATLAB converts MRIs into matrices. According to the statistics, the recommended technique has 73% diagnostic accuracy. Depending on the authors' "smoothing factor," accuracy may be greater.[6]

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3. PROPOSED SYSTEM

The proposed methodology has the flow is as shown in the figure 2. The architecture for the employed convolutional neural network is as shown in the below figure

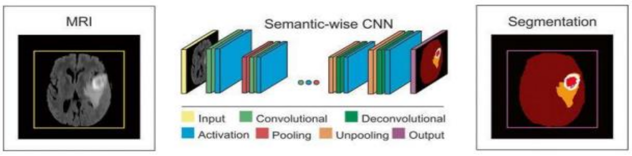

Figure 1: Architecture of the CNN.

The details of the architecture employed in the CNN is briefed in this section.

3.1 Convolutional layer: it is the layers which has the numerous layers of filter to reduce the dimension of the image.

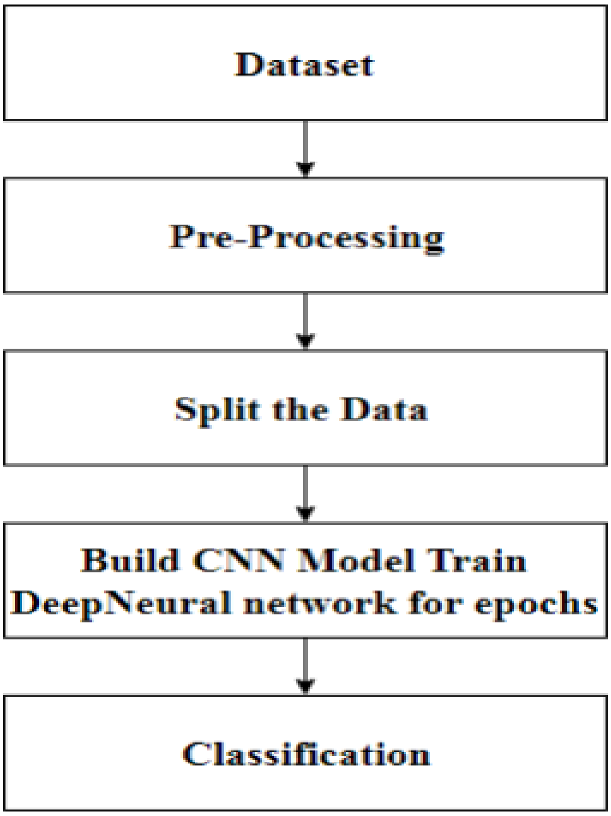

Figure 2: Proposed flow diagram.

3.2 Maxpolling: it allows only to pass the largest pixel of the matrix.
3.3 Dropout: to avoid the overfitting this layer is employed, randomly the unwanted neural connections are removed from the model.
3.4 Flatten: it is used to perform the vectorization process, which is used to convert the image to one row array elements.
Activation: the non-linear activation function is employed to convert the pixels into the probability of -1 to 1. The activation function used for implementation is sigmoid.

3.5 Employed dataset: The employed dataset has the five hundred fifty-six images in the dataset which possess the tumour [7]. The sample images employed for the model is as shown in the below figure,

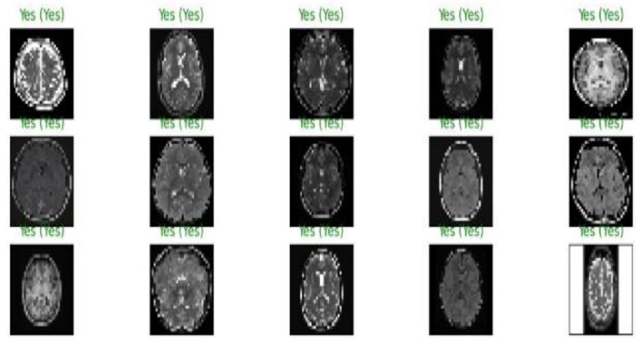

Figure 3: Images of dataset.

4. RESULT AND DISCUSSION

This section provides the details of the result obtained during the implementation process,
The labels for the images employed in implementation is as shown in the below figure,

```
<built-in function dir>
/content/drive/My Drive/brain_dataset/yes
X_data shape: (235, 224, 224, 3)
y_data shape: (235,)
<built-in function dir>
/content/drive/My Drive/brain_dataset/no
X_data shape: (413, 224, 224, 3)
y_data shape: (413,)
```

Figure 4: Labels generated for the image.

The resized image's dimensions of the input images is as shown in the below figure,

```
X_data shape: (330, 224, 224, 3)
X_data shape: (83, 224, 224, 3)
Y_data shape: (330,)
Y_data shape: (83,)
```

Figure 5: Dataset splitting of images.

The training process along with the accuracy for every epochs is as shown in the below figure,

```
Epoch 245/250
15/15 [==============================] - 48s 3s/step - loss: 0.4972 - accuracy: 0.7542 - val_loss: 0.5175 - val_accuracy: 0.8485
Epoch 246/250
15/15 [==============================] - 48s 3s/step - loss: 0.5008 - accuracy: 0.7374 - val_loss: 0.5198 - val_accuracy: 0.7879
Epoch 247/250
15/15 [==============================] - 52s 3s/step - loss: 0.4825 - accuracy: 0.7879 - val_loss: 0.5250 - val_accuracy: 0.7879
Epoch 248/250
15/15 [==============================] - 48s 3s/step - loss: 0.4977 - accuracy: 0.7407 - val_loss: 0.5130 - val_accuracy: 0.8182
Epoch 249/250
15/15 [==============================] - 48s 3s/step - loss: 0.4789 - accuracy: 0.7542 - val_loss: 0.5168 - val_accuracy: 0.8788
Epoch 250/250
15/15 [==============================] - 48s 3s/step - loss: 0.4849 - accuracy: 0.7441 - val_loss: 0.5262 - val_accuracy: 0.7879
```

Figure 6: Training process for the model.

The accuracy of model for the testing process is as shown in the below figure,

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```
scores=model.evaluate(xTest, yTest)
print("%s: %2f%%" %(model.metrics_names[1], scores[1]*100))
```

```
3/3 [==============================] - 2s 808ms/step - loss: 0.5499 - accuracy: 0.8072
accuracy: 80.722892%
```

Figure 7: Accuracy of the model in testing phase.

The summary of the proposed model is as shown in the below figure,

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 16)        3904
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 16)        0
_________________________________________________________________
dropout (Dropout)            (None, 16, 16, 16)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 16, 16, 16)        20752
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 16)          0
_________________________________________________________________
dropout_1 (Dropout)          (None, 8, 8, 16)          0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 8, 8, 36)          46692
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 4, 4, 36)          0
_________________________________________________________________
dropout_2 (Dropout)          (None, 4, 4, 36)          0
_________________________________________________________________
flatten (Flatten)            (None, 576)               0
_________________________________________________________________
dense (Dense)                (None, 512)               295424
_________________________________________________________________
dropout_3 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 513
=================================================================
Total params: 367,285
Trainable params: 367,285
Non-trainable params: 0
```

Figure 8: Model summary.

Predication of the brain tumour by the model is as shown in the below figure,

```
[[0.]]
No
```

```
[[1.]]
Yes
```

4. CONCLUSION

One of the greatest methods for evaluating picture datasets is CNN. The CNN reduces the size of the picture without sacrificing any of the information necessary to make accurate predictions.

Using picture augmentation methods and assessing the ANN and CNN's performance, the same thing may be accomplished. Using the trial-and-error approach, this model was built up here.

The number of layers and filters that may be utilized in a model can be optimized in the future using optimization methods. As of today, CNN is the best method for predicting the existence of a brain tumour for the supplied dataset.

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