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An Enhanced Deep Learning Model for Brain Tumor Prediction

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Abstract— Brain tumour diagnosis & prediction is an challenging issue and important area of research. perversely, convolutional neural networks can support this (CNNs). They have mastered computer vision problems as well as other issues like segmenting, detecting, and recognizing visual objects. By enhancing the brain images with help of segmentation methods that are extremely challenging related to noise and cluster size sensitivity issues, as well as automated region of Interest detection (ROI), it helps with the diagnosis of brain tumours. The reality that CNNs have achieved high level of accuracy and it does not require manual extraction of features. Finding a brain tumour and correctly classifying it are challenging tasks. CNN outperforms rivals due to its extensive use in image recognition. Brain tumour segmentation is the most significant and challenging problems in the field of medical image processing research because human assisted manual categorization may lead to inaccurate prediction and diagnosis. In addition, when there is a huge amount of data existing to support in the process, it is challenging. Extraction of tumour areas from images becomes challenging due to the wide variety of appearances of brain tumours and the similarity of tumour and normal tissues.

Keywords- Deep Learning, CNN, segmentation, Region of Interest (ROI)Brain Tumor.

1. INTRODUCTION

We are now living in a time when disease rates are rising dramatically. One of the most dangerous diseases is a tumour, which is a lump that can develop anywhere on the body. The brain tumour is the most severe type of cancer and can appear anywhere in the brain. It is generally defined as abnormal brain cell growth. These abnormal brain cells have the potential to harm normal brain cells, leading to brain dysfunction. Brain tumours can take many different shapes. These tumours may be benign (noncancerous) or malignant (cancerous) (not cancerous). It is very difficult task to find a tumour that precisely determine its kind [2].

A result of CNN's extensive use in image recognition, it performs better than the competitors. In essence, it consists of a group of neurons with learnable weights. Additionally, they are known for performing and executing with extraordinary accuracy. The noise and irregularities in the image might make it difficult for humans to accurately forecast the presence of a tumour. This is what motivates us to work on an algorithm to anticipate tumours. "There are techniques in this for locating tumours and classifying them as normal, malignant, or benign"[3].

Radiomics has progressed as a vital regimen for guessing survival lengths by misusing countenance visage to a degree the arithmetic of domains of interest and the makeup and force of individual pixels. The advancement of these approaches has emphasize the increasing need for mechanical separation. Notably, distinctnesses arose in the first and second authors' manual, confuse hand segmentations of intellect tumours. "The Srensen-Dice cooperative, a freely approachable rhythmical of separation characteristic, was premeditated utilizing the Studier Fenster calculator to analyze the thickness of picture separation"[4].

"The consequence came from the separation attended by the first and second authors allowed a score of 0.91, reveal the alternative in manual separation"[5]. This article will look at the application of CNN for low-grade diffuse astrocytoma (WHO grade 2) and high-grade glioblastoma (WHO grade 4), which is also known as glioblastomamultiforme (GBM)

Because of the variety of clustering methods that are currently accessible and well recognized, the brain was explored. "Machine learning is boosting quickly, win fame at main conferences. Radiologists need to assert an conversant view. This research project offers a different blend of informative pieces and an far-reaching test of convolutional affecting animate nerve organs networks in the context of glioblastoma"[4].

2. LITERATURE SURVEY

i ***Neelum Nooren et at.., Malaysia 2ImViA Laboratory, Jan 21, 2020***, Detecting intellect lump images in MRI scans is a disputing task on account of the various and intricate type of tumors. "This study presents two discovery methods: the first involves beginning edge discovery and separation, while the second leverages the ability of fake affecting animate nerve organs networks (ANN). Within the targeted Neural Network approach, the process includes range decline, feature origin, detection, separation, and categorization. The projected strategy for intellect cyst labeling and segmentation displays superior veracity and fame in this place research"[2].

ii ***.Natl et at., Cancer Institute, Vol. 85, No. 5, pp. 365-76*** The questionnaire took an average of 11 minutes to complete, and most patients did not require any assistance. With the exception of role functioning, which was the only multi-item scale that did not match the minimal requirements before or during therapy, the findings confirmed the questionnaire's expected scale structure. Three findings demonstrated the validity of the study.

iii ***chidambaram. T. et.., Sep 2017, "Brain tumor segmentation using genetic algorithm and ANN techniques. International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI) (pp. 970-982) [4]".*** In many symptomatic and curative applications, automatic problem identification in MR images are critical. "Tumor segmentation and classification are difficult due to the large amount of data in MR images and the fuzzy borders. This research has developed an automated brain tumour detection approach that improves precision and yield while reducing diagnosis time. The purpose is to divide tissues into two categories: normal and pathological"[2]. The suggested approach may successfully detect the shape of the tumour as well as its geometrical dimensions. Furthermore, a manipulation approach is designed to carry out an automatic brain tumour categorization utilising MRI-scans based on finding vector quantization using that picture and data analysis. The cost of training, classification accuracies, and computing time are used to evaluate the altered ANN classifier execution. "Due to the variety and complexity of tumours, detecting MRI brain tumour pictures is a tough process. This study introduces two detection techniques: the first is edge detection and segmentation, and the second is Artificial Neural Network proficiency"[4].

3. ANALYSIS

3.1 EXISTING SYSTEM

"Various plans have existed working for brain cyst disease, including pre-prepared models, various Convolutional Neural Network architectures, and ensemble models that amalgamate diversified models, as described in Table 1[5]". As noted in the previous section, current systems have several flaws. A Genetic Algorithm was successfully implemented in the existing system After capturing multiple training samples and comparing them with ideal edge images, this algorithm provides the best edge filter and thresholding.

Table1: Comparision with other techniques

Features	Model	Accuracy (%)
Model based	CapsNet	86.56
Model based	CNN	84.19
DWT-Gabor	NN	91.90
CNN	ELM	93.68

"Previous methods encountered challenges accompanying images holding explosion, such as alternatives in lighting, blurriness, and occlusions. Furthermore, few of these existing structures struggled to realize authentic-time labeling due to restraints related to restricted datasets"[6].

3.2 PROPOSED SYSTEM

The structure of neural network mimics how the human brain works. data clustering, Vector quantization, optimization functions, pattern matching, and different types of classification methods employ neural networks.

An MRI image dataset is initially gathered and preprocessed, after which these pictures are trained using a CNN model to extract features, and lastly it determines the stage of cancer as shown in Figure 1.

Images can be scaled using CNN. This system consists of an input layer, convolution layer(CN), Rectified Linear Unit (RLU) layer , pooling layer (PL), and a fully connected (FC) layer. The convolution layer divides the input image into pieces. each component is then activated by ReLU layer individually, pooling layer is optional. Based on a likelihood ranging from 0 to 1, a fully connected layer is utilised to determine the class score or label score value as shown in Figure 4.

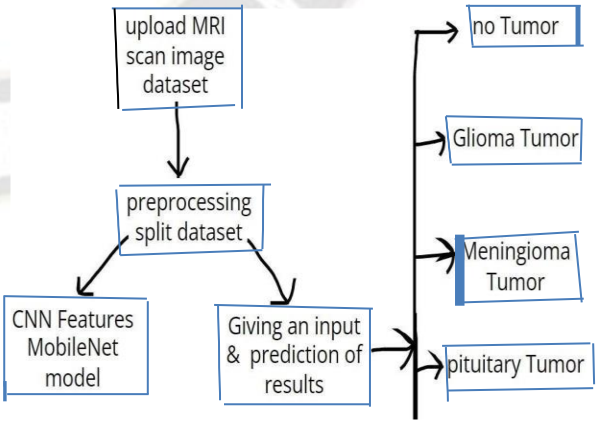

Figure 1: Block Diagram

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3.2.1ARCHITECTURE

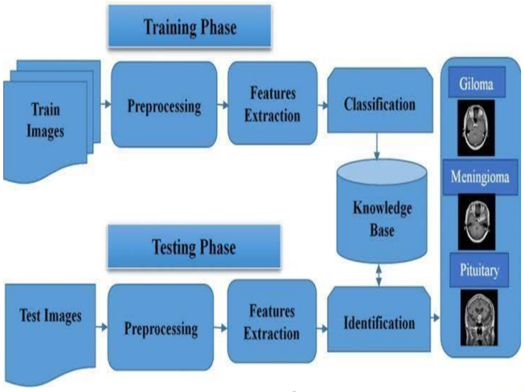


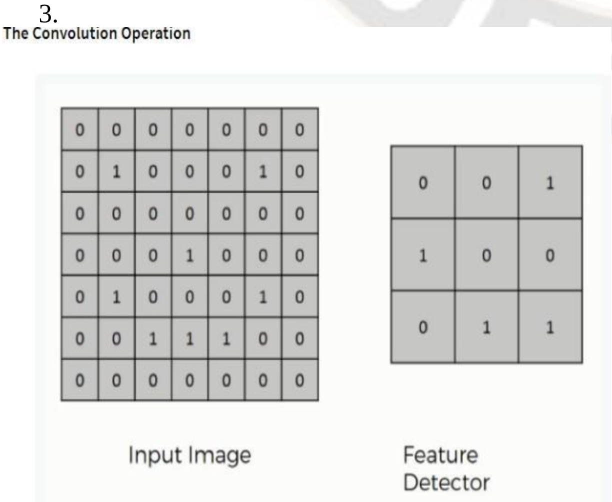
Figure 2: Architecture Diagram

Figure 2 above shows the model's architecture, including how pictures may be trained, evaluated, and classified into several classes.

3.2.2CONVOLUTIONAL NEURAL NETWORK (CNN)

Deep learning neural networks like the CNN are frequently utilised for image processing and classification. As feed forward networks, CNNs allows information to travel in only one way, from their inputs to their outputs. In contrast to other classification algorithms, this algorithm can be able to distinguish between one and the other image. The primary advantage of CNN over rivals is the automatic feature recognition carried out without any human error. Convolutional, pooling, and fully linked layers are used to construct the CNN architecture. A FCL comes after a convolutional layer and follow by a subsequent convolutional & pooling layers. These layers are placed one above the other to create a new deep learning model [1].

- **Convolutional layer***: CNN* extracts the characteristics from the given i/p image. It has a matrix of integers called kernels, which are learnable filters (trainable weights). In order to create a feature map, the filter conducts a dot product on the area of the picture that it is lingering over while shifting by a stride throughout the image. "Within the unchanging coating, distinct feature maps own variable weights, allowing for the ancestry of diversified visage at each location"[4].as shown in figure 3.



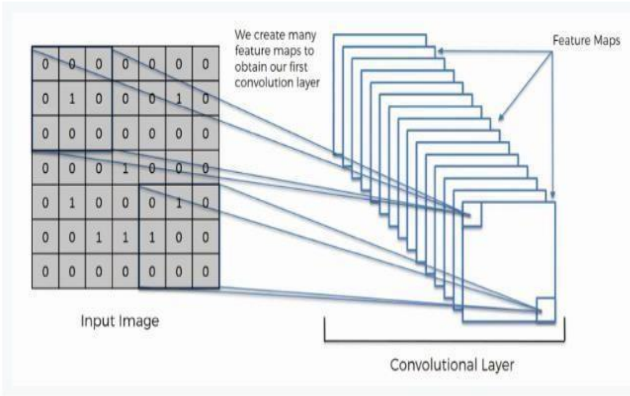


Figure 3 Convolution matrix

- **Pooling layer*:*** This layer is utilised to choose the best features and lower the dimensionality of the feature maps. In this layer, Unlike the convolutional layer, which has weights, it process sweeps a filter over the whole i/p. "The filter applies an aggregate function on the values in their respective fields, resulting in the generation of an output array. "[1].

There are 3 different types of pooling methods:

i) **Max Pooling*:*** It is a function that select the pixel from the chosen i/p part with the highest value.

ii) **Average Pooling:** It is a function that computes the mean of each pixel in the selected input region and delivers that value to the output array.

iii) **Flattening:** Convolutional neural networks' flattening technique describes how we may alternate between pooling and flattened layers.

In the proposed system Max Pooling is used for dimensionality reduction of image.

- **Fully Connected layer*:*** In this layer every neuron in each layer is connected to the next layer via feed-forward neural network. This layer accepts an input the flattened output of the pooling layers. FC layer serves as a classifier to categorize the given i/p image, for this purpose it employs an activation functions like SoftMax & Sigmoid [1]. In the paper we used, SoftMax activation function.

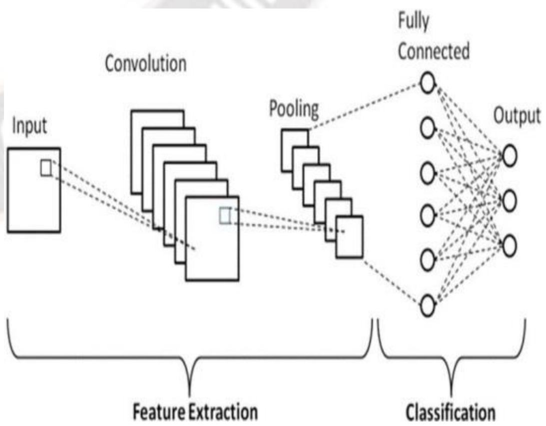


Figure 4 General CNN architecture

4. IMPLEMENTATION

4.1 DATASET

The suggested approach makes use of brain tumour MRI scan pictures obtained from an open-access dataset publically available on Kaggle. This dataset contains 3,264

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photos, with 2,860 images utilised for model training and 404 for testing. These photos are divided into four categories: As stated in Table 2, which shows the distribution of pictures for both training and testing, Class-1 represents glioma tumours, Class-2 represents meningioma tumours, Class-3 represents pituitary tumours, and Class-4 indicates the lack of tumours.

Table 2: Training and Testing Dataset Images

	Training Dataset		**Testing Dataset**	
Class	**Emotion**	**No. of images**	**Emotion**	**No. of images**
Class-1	giloma	826	giloma	100
Class-2	Menungiama	822	menungioma	115
Class-3	pituitay	827	pituitary	74
Class-4	No Tumor	395	No Tumor	105

Figure 5 below shows an example of the code for training and evaluating the model with various accuracy epochs.

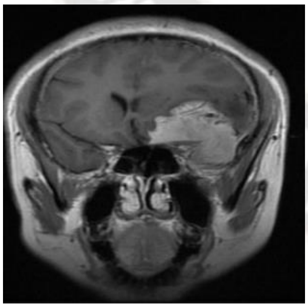
```
test_set = train_datagen.flow_from_directory('C://Users//saitu//OneDrive//Desktop//dataset//Testing',
                                             target_size=(224,224),
                                             batch_size=32,
                                             class_mode='categorical')
89/89 [==============================] - 155s 2s/step - loss: 0.0518 - accuracy: 0.9841
Epoch 34/35
89/89 [==============================] - 162s 2s/step - loss: 0.0415 - accuracy: 0.9908
Epoch 35/35
89/89 [==============================] - 152s 2s/step - loss: 0.0266 - accuracy: 0.9944

model.compile(optimizer='Adam',loss='categorical_crossentropy',metrics=['accuracy'])
step_size_train=train_generator.n//train_generator.batch_size
history=model.fit_generator(generator=train_generator,
                  steps_per_epoch=step_size_train,
                  epochs=35)
```

Figure 5: sample code and accuracy epochs

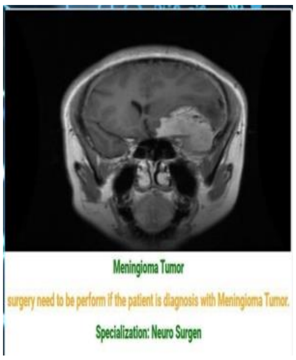
5.RESULTS

The output of the model is an image and shows that tumour is present or not and also suggest the specialist as shown in figure 6

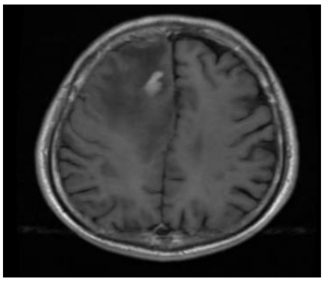
SampleInput1:



Output:



SampleInput2:



Output:

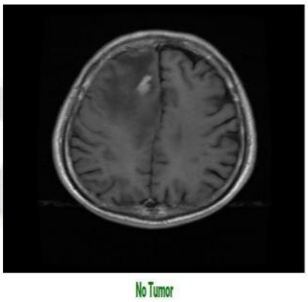


Figure 6: Training and Testing Graph

5.2PERFORMANCE EVALUATION:

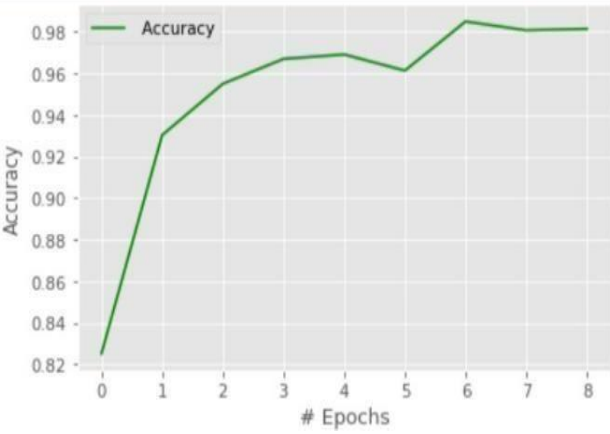


Figure 7: Accuracy Graph

As the number of epochs increase the accuracy also increases gradually and at one stage it becomes constant as shown in figure 7.

TABLE 3: COMPARISON OF EXISTING AND PROPOSED SYSTEMS

Features	Model	Accuracy (%)
Model based	CapsNet	86.56
Model based	CNN	84.19
DWT-Gabor	NN	91.90
CNN	ELM	93.68
CNN	MobileNet	96.61

From the above table 3 we made conclusions that our proposed MobileNet Model made approx. 96.61percent and brings accurate results. These accuracy is being calculated from each Epochs we get during execution of our model and totally we run 35 epochs.

6.CONCLUSION AND FUTURE SCOPE

6.1 CONCLUSION

Thereby it is concluded that the project is determined for the purpose of recognition of tumour cells among brain with the provided MRI scanned pictures by the help of CNN layers. This model even performs well in detecting giloma tumor, menungioma tumor, pituitary tumor, and non tumor scans among the opted images(MRI scans). The CNN features and the MobileNet model are employed. To classify the tumors, image enhancement techniques, a Convolutional Neural Network (CNN) model, and a Softmax Classifier were employed, resulting in an impressive accuracy rate of 96.6 percent. In terms of detecting brain cancers, the suggested method outperforms several current techniques.

6.2 FUTURE WORK

In the future, we'd like to expand our model to include photos with various sorts of body tumors, blurring, and occlusion

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