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Profound Learning Approach for Brain Tumor Location and Segmentation

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ABSTRACT: A brain tumour is a dangerous medical illness that, if not treated promptly, can be fatal. An integrated technique is used to detect brain cancers through image processing. The goal of this project was to present a system that could categorize and detect brain cancers from MRI images using the CNN algorithm and deep learning techniques. Pre-processing and segmentation were used to improve the images, which were obtained from an MRI image dataset. Because the suggested method takes fewer resources, our neural network design is easier to train and execute on another computer. As a result, early detection of the tumour is required in order to schedule therapy as soon as possible. In this study, we present a CNN model for brain tumour identification. To begin, brain MRI scans are enhanced in order to gather enough data for deep learning. After that, the photos are pre-processed to reduce noise and prepare them for the next stage. The proposed system is trained on pre-processed MRI brain pictures and uses features derived during training to classify newly input images as tumorous or normal.To create the image, autoencoders are utilised to remove irrelevant features, and the tumour region is then segmented using the KMeans technique, which is an unsupervised learning method.

Keywords—brain tumor, CNN, MRI, noise, tumors, autoencoder, K-Means algorithm, unsupervised learning.

I. INTRODUCTION

The human body has many different types of cells, each with its own function. Cells divide and expand in a controlled manner to produce new cells, which is required to maintain our bodies healthy. When cells lose their ability to grow and divide normally, they expand in an un-organised and uncontrolled manner, resulting in a mass of tissue known as a tumour. A brain tumour is a lump of tissue in the brain that contains aberrant cells. Tumors can be benign or malignant; benign tumors are not cancerous, but malignant tumors are. Although some tumors are not malignant, it is critical to diagnose them early in order to begin adequate therapy. A radiologist examines MRI scans to look for abnormalities and make conclusions in the standard way of detecting brain tumors. Because these photos contain many anomalies or noisy data, a radiologist will struggle to analyse them in a limited amount of time. It becomes increasingly difficult to analyse large amounts of data as the size of the data grows. Image processing can lower the amount of noise in these images, making them easier for a machine to understand and analyse. Intensity difficulties in MRI pictures can be reduced to a degree by image processing, allowing computers to perceive things that the naked eye cannot. CNN is one of the deep learning techniques that can be used to detect cancers. CNN has a wide range of applications, including facial recognition, image analysis, classification, climate comprehension, and many others. In the real time of image categorization, CNN is extensively used. The suggested approach combines a simple CNN that categorize brain MRI images as tumorous or normal with an Auto-encoders method that outputs an image with fewer feature dimensions. The K-Means algorithm is also used to segment auto-encoder generated images that are over-layed over the source image. This method eliminates the need for human intervention in tumour detection and segmentation, saving both money and time.

II. RELATED WORK

Hussna Elnoor Mohammed Abdalla[1] suggested a CAD (Computer Aided Detection System) for classifying an MRI resonance image dataset obtained from the Whole Brain Atlas.This system's website. It was first difficult to load the MRI image.is preprocessed before being segmented using a threshold. Then For feature extraction, statistical feature extraction is utilised.

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Finally, the suggested ANN model is used to classify input data from the brain. Is the MRI image of a tumour or a non-tumor? Precision and sensitivity. The results reported in this paper are 99.9% and 97.9%, respectively.

Tonmoy Hossain[2] presented two methods for segmenting and detecting brain tumours. For tumour detection, the first model uses FCM for segmentation and standard classifiers such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Nave Bayes, and Random Forest. The above-mentioned classifiers were compared on several performance characteristics such as accuracy, recall, precision, and so on, and it was discovered that SVM outperformed the other traditional classifiers with a detection accuracy of 92.42 percent. The proposed 5 layer CNN model gave a detection accuracy of 97.87 percent in the second model, which was based on convolution neural networks (CNN).

M. Al-Ayyoub, Husari et al.,[3] created a model that uses MRI scans to detect brain tumors. The MRI images are divided into two categories: those with tumors and those without tumors. Image and MATLAB are two popular programs they utilize for this. To detect the tumour, they extract 10 separate features from each image.

[4] Komal Sharma, Akwinder Kaur, and others. When paired with feature extraction techniques, MR human brain pictures are identified using supervised approaches like artificial neural networks and support vector machines, as well as unsupervised techniques like self organization map (SOM) and fuzzy c-means.

L. Kapoor et al. [5] examined various strategies utilized in each phase of image processing. Noise reduction and noise removal, image reconstruction, grayscale conversion, and image enhancement are all examples of pre-processing. They discussed a variety of image sharpening and smoothening algorithms, including the Median Filter, Gaussian Filter, and others. In the segmentation phase, Otsu thresholding, Genetic Algorithm, k means Clustering, and Watershed Segmentation are some of the approaches mentioned. The benefits and drawbacks of various segmentation strategies were also explored by the author. The final section of this survey article discusses numerous image processing techniques utilized in medical image processing.

III. PROPOSED ALGORITHM

A.DATABASE:

Kaggle was utilised to obtain the dataset for training and testing. It includes a total of 253 MRI brain images. There are 155 tumorous images and 98 normal images among them (without tumor). Normal images are kept in the "no" folder, while tumorous images are kept in the "yes" folder. Images come in a variety of sizes and formats.

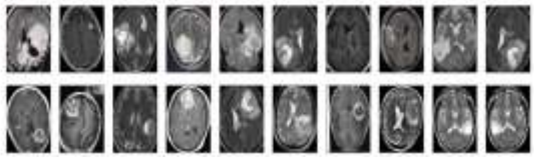

Fig. 1. **S**amples of the dataset

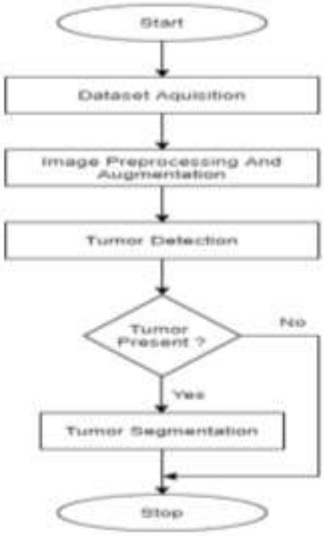

Fig.2. Flowchart

B.Pre-processing of images

As previously stated, the collection contains photos in various formats and sizes, some of which may contain noise. This can result in classification and segmentation mistakes. Pre-processing the image will almost certainly solve this issue, and the data can be translated into a standard format that can be used for classification and segmentation. Greyscale images with a fixed size of 256x256 pixels are transformed. To decrease noise, the photos are blurred with Gausian blur. The photos are also processed through a high pass filter, which sharpens the image and allows for the extraction of more complex elements.

C.Augmentation of images

The dataset contains insufficient data to be used as CNN training data. As a result, the augmentation approach is employed to correct the imbalance. Augmentation is a method for combining statistical data into a model. This programme can create a variety of two-dimensional images with different poses and sizes. The use of

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augmentation to obtain image variants can help to improve CNN segmentation accuracy. For reliable findings, deep learning necessitates a huge dataset. Image
augmentation is a method of extending the amount of a dataset by creating duplicates of images using various processing techniques such as random rotation, shifts, shear, and flips.

D. CNN Model

1) Architecture for tumor detection:

The pre-processed image is loaded into a CNN model, which contains an input layer, convolution layers, and a fully connected layer that activates a certain neuron to produce a specific output or decision. The input layer is made up of the input image. A 256x256 pixel matrix is used to represent the image. Each pixel exhibits different characteristics. The first convolution layer applies 8 filters of 3x3 size kernels each to the input image by sliding through the position one by one, yielding a total of 8 feature maps. This process is known as feature extraction. These characteristics are then given into the ReLU activation function, which applies a threshold operation to each input element, setting values less than zero to zero. The output of the ReLU layer is applied to a max pooling layer with a 2x2 window size, resulting in down sampling the feature maps to 128x128
Xavier Weights in the network are set up via initialization.Cross-entropy is a measurement of the difference between the actual and projected results. Using the chain-rule of differentiation, the Adam optimizer propagates this error back through the Network and adjusts the filter-weights to improve the classification error. Back-propagation is the term for this technique, which is repeated iteratively until the classification error is significantly reduced. Overfitting can occur during training when the model learns the features and noise in the data used for training and influences the model's performance on fresh, unseen data. In fully-connected layers, a dropout function is utilized to prevent overfitting. Dropout is a regularisation approach in which some units are dropped at random, i.e. set to 0 at a set rate. To reduce overfitting, 60% of the units in the proposed model are removed.

2) Auto-Encoder Image Generation Architecture:

Because the dataset used to train the proposed model does not offer ground truth segmentation findings, unsupervised learning is used for tumour segmentation. Unsupervised learning can be used to segment data in a variety of ways; for our suggested model, we are employing Autoencoder. Autoencoder is an unsupervised learning technique that learns to compress data effectively with an encoder and then rebuild the data with a decoder in such a way that no crucial data is lost during the decoding phase. The decoded data that was generated from the encoded data looks quite similar to the input image. The output image has the same dimensions as the input image. The decoded image has the same appearance as the input image, but it contains just the significant aspects of the image and hides the noisy data. As a result of the encoding and decoding processes, undesired noise can be eliminated, improving the accuracy of pinpointing the region of interest. Three convolution layers make up the encoder. The first Convolution layer takes the tumorous image as input and applies 16 3x3 kernel size filters with a stride of 1 to generate 16 256x256 feature maps that are supplied to the ReLU activation function, followed by a max-pooling layer that shrinks the feature map to 128x128 pixels.
Second Convolution uses ReLU activation to generate 8 feature maps of 128x128 pixels, which are then sent to the max-pooling layer, which decreases the feature map size to 64x64 pixels. Third Convolution uses 8 3x3 kernel size filters to generate 8 64x64 pixel feature maps, which are then fed to a max-pooling layer, which reduces the feature map size to 32x32 pixels. The Decoder is made up of three de-convolution layers, each using a 3x3 kernel and a stride of two to reconstruct the image with less and more essential information. The image is up-sampled to 64x64 pixels using 8 feature maps in the first decoder layer. The second decoder generates eight 128x128 pixel features maps, which are supplied to the third decoder layer. The image is up-sampled to 256x256 pixels in the third layer, which generates 16 feature maps. The output layer of the autoencoder receives the result of the third decoder layer. From the feature maps created by the third decoder layer, this layer builds the image. The final convolution layer's output is a compressed image, which means that irrelevant features are removed and the image is represented with smaller feature dimensions. To accomplish segmentation, the output image is superimposed over the original image.

3) Post-Processing (Tumor Segmentation):
Clustering is one of the most extensively used data analysis methods in a variety of emerging-areas applications. Clustering is the process of identifying groupings of things in which the objects in each group are similar to one another but distinct from those in other groups. This is a good clustering method because it produces high-quality

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clusters with high intra-cluster similarity and low inter-cluster similarity. We must first define the number of clusters k in the k-means algorithm. Then, at random, the kcluster centre is picked. The distance between each pixel and the centre of each cluster is determined. The distance could be calculated using a simple Euclidean function. The distance formula is used to compare a single pixel to all cluster centres.The autoencoders' overlayed image is used for tumour segmentation. This image just shows the most significant details, making it easy to segment the tumour area. After that, the image is normalized so that all of the pixel values are between 0 and 1. The final segmentation is done using the K-means unsupervised technique. The K-means algorithm divides the image into two clusters iteratively during this procedure. To obtain a binary image with segmented tumour region, the K-means method is performed 40 times.

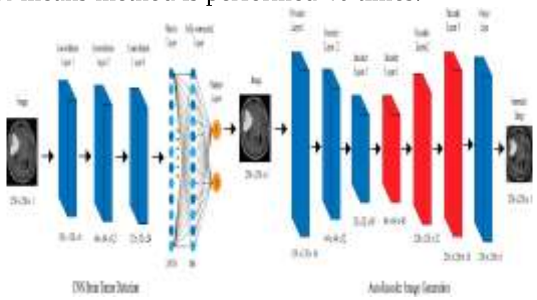

Figure 3. Proposed architecture

IV. RESULTS

A. CLASSIFICATION RESULTS

The proposed approach correctly classifies brain MRI images as shown in Figure 4. If the image contains tumour (True: 1), the model also predicts that it contains tumour (Pred: 1), and if the image does not contain tumour (True: 0), the model predicts that there is no tumour or that the image is normal (Pred: 0).

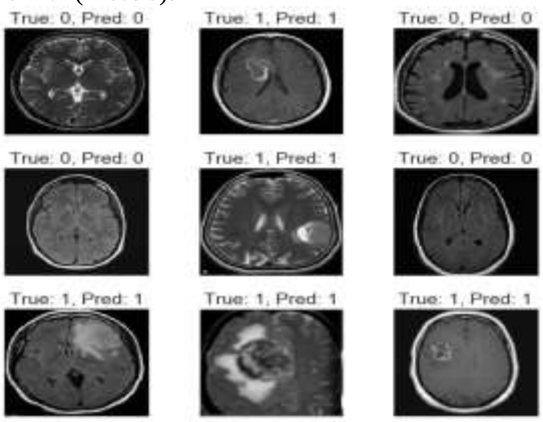

Figure 4. Classification results

The suggested model misclassifies brain MRI images as seen in Figure 4. If a picture has tumour (True:1), the model predicts that it does not contain tumour (Pred: 0), and if it does not contain tumour (True: 0), the model predicts that it does have tumour (Pred: 1).

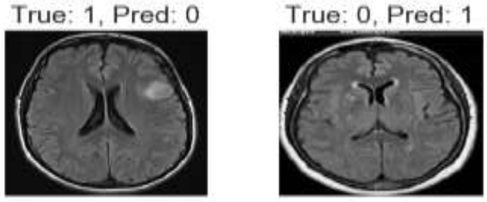

Figure.5. Missclassified image

The confusion matrix in Figure 6 depicts the performance of our brain tumour detection model. From the same, the following performance measurements may be generated.

$$\text{Accuracy} = \frac{TN+TP}{TN+TP+FN+FP} = 95.55\% \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} = 96\% \quad (2)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} = 96\% \quad (3)$$

$$\text{F1 Score} = \frac{2 \times TP}{2 \times TP+FP+FN} = 96\% \quad (4)$$

Where TN = true negative, TP = true positive, FN = false negative, FP = false positive.

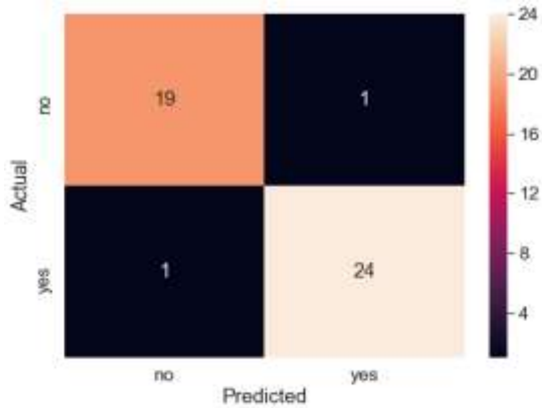

Figure .6. Confusion matrix

Results of Segmentation:

Images with tumors are split to find the tumor's location. Table I shows tumorous brain MRI images that have been appropriately segmented, with the tumour region clearly apparent and noise-free. The first column comprises tumor-detected MRI scans of the brain (tumorous images). These images are run through autoencoders, and an image is formed; the second column in the table represents the same, i.e., each tumorous image's generated image. These images

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are superimposed over the source photographs to create new ones. This is referred to as image overlay. In the third column, you'll find image overlays. Finally, K-means is performed to the Image overlays photos to pinpoint the tumour region. The segmented photos are shown in the table's last column.

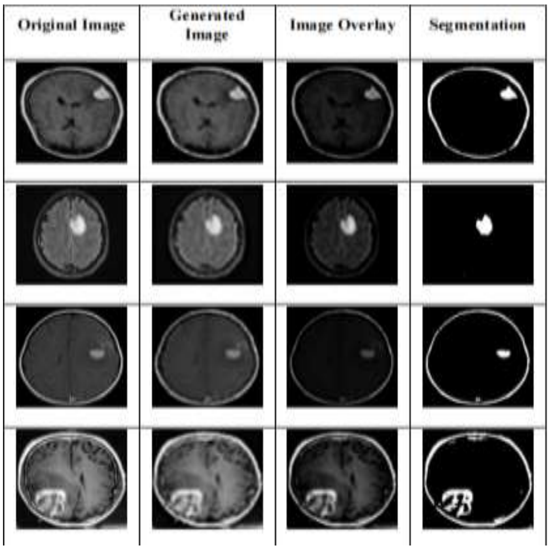


TABLE I. SEGMENTATION RESULT

Table II represents Tumorous brain MRI images that are not properly segmented where the tumor region is visible but along with some noise which makes the quality of segmentation poor.

TABLE II. SEGMENTATION WITH NOISE

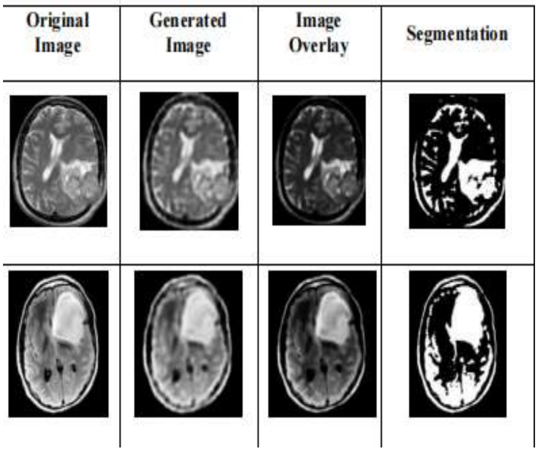
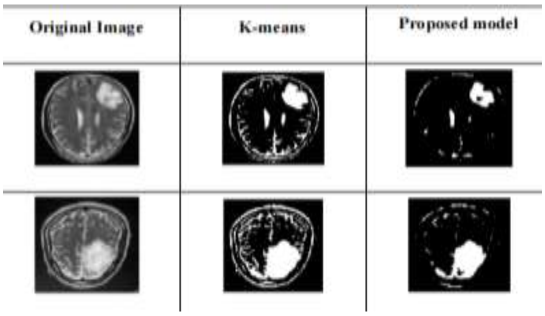


TABLE III. COMPARISON OF SEGMENTATION WITH K-MEANS AND PROPOSED MODEL(AUTOENCODERS + K-MEANS)



V. CONCLUSION

The time-consuming process of detecting brain tumors is thus made easier by automation. The proposed model for detecting brain tumors has a testing data accuracy of 95.55 percent. Following the detection of the tumour with convolutional neural networks, segmentation techniques such as autoencoders and K-means are used to pinpoint the tumour in the image. When segmenting the tumour image directly with K-means, as illustrated in Table III, it can result in a noisy, poorly segmented image. As a result, we integrated Autoencoders with K-means for segmentation, which resulted in more exact and clear segmented images with less noise. As a result, an effective model for detecting and segmenting brain tumors is developed, saving both human work and time.

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