



BRAIN TUMOR DETECTION IN MRI USING CNN.

DR.J.B. JONA ^[1], MUTHUKUMAR I ^[2], PRAVEENA V ^[3],

VIJAYASHREE P ^[4]

Associate Professor ^[1] & Student ^{[2],[3],[4]}

Department Of Computer Application

Coimbatore Institute of Technology

ABSTRACT:

Automated fault detection in medical imaging has become a hot issue in a range of medical diagnostic applications. Magnetic Resonance Imaging (MRI) automated tumour diagnosis is crucial because it provides information about abnormal tissues that is needed for therapy planning. The traditional method for finding flaws in magnetic resonance brain imaging is human inspection. This method is unworkable when dealing with large amounts of data. As a result, radiologists are developing automated tumour detection methods in order to save time. MRI brain tumour identification is difficult due to the intricacy and variety of tumours. Using CNN, This Paper detect whether an MRI picture is a tumour or not in our suggested work. In this Project use frontend and backend are used. On the frontend, we utilised DJANGO in Python to create the Web Application, and on the backend, we trained the model using 3000 photos and completed the testing phase.

Keywords: *Magnetic Resonance Imaging, Convolutional Neural Network, Artificial Neural Network, Django, image classification.*

I.INTRODUCTION:

The human body consists of the many forms of cells. Each cell features a specific function. The cells within the body grow and divide in an orderly manner and form some new cells. These new cells help to stay the build healthy and properly working. When some cells lose their capability to manage their growth, they grow with none order. The additional cells formed form a mass of tissue which is named tumour. The tumours are often benign or malignant. Malignant tumours cause cancer while benign tumours aren't cancerous consistent with a report published by Central Tumour Registry of the US (CBTRUS), approximately 39,550 people were diagnosed with benign and malignant brain tumours in 2000. It indicates that the speed of primary tumour whether tumour or non-malignant tumour is 14 per 100,000. The

important factor in the medical diagnosis includes the medical image data obtained from various biomedical devices that uses different imaging techniques like X-ray, CT scan, Magnetic Resonance Imaging (MRI) is a technique which depends on the measurement of magnetic field vectors that are generated after an appropriate excitation of strong magnetic fields and radio frequency pulses in the nuclei of hydrogen atoms present in the water molecules of a patient's body. The MRI scan is much better than CT scan for diagnosis as it doesn't use any radiation. The radiologists can evaluate the brain using MRI. The MRI technique can determine the presence of tumor in the brain.

Upgrades in database innovation, figuring execution and man-made brainpower have added to the improvement of clever information investigation. The Support Vector Machine has been created as a hearty apparatus for order and relapse in loud, complex spaces. Not at all like conventional strategies which limit the observational preparing mistake. Bolster Vector Machine goes for limiting an upper

bound of the speculation mistake through amplifying the edge between isolating hyper plane and the information.

Following that, the paper is arranged as follows: Following the introduction of Brain Tumors in Sections 1, Section 2 covers the research background and Related activities. The third section provides the Proposed Methodology. Overview of Conventional Neural Network is presented in Section 4. Section 5 presents Front-end Process using Django. In Section 6, Model and Training phase. In section 7, Experimental Result Analysis. section 8 presents conclusion.

II. RESEARCH BACKGROUND AND RELATED WORK:

The brain is a vital organ within the form which control and coordinates the tasks distributed by the opposite parts of the body. it's primarily the center of the central systema nervosum and is to blame for performing the daily voluntary and involuntary activities within the body. The tumour could be a fibrous mesh of unwanted tissue growth inside our brain that proliferates in an unconstrained way. to stop and to cure the tumour, resonance imaging (MRI) is widely employed by radiologists to research stages of brain tumours. The results of this analysis reveal the presence of the tumour.

The use of ANN has been used to construct a Brain Cancer Detection and Classification System in this paper^[1].

Histogram equalisation, picture segmentation, image enhancement, and feature extraction were among the image processing techniques employed. When compared to other

classifiers, the suggested approach using ANN as a classifier for classification of brain pictures has a high classification efficiency. Sensitivity, specificity, and accuracy have all been enhanced. The proposed method is efficient in terms of computation and produces decent results [3].

Hough voting is a mechanism for totally automatic localization and segmentation of anatomical structures of interest, and it was utilised in this investigation. It also employs a robust, multi-regional, versatile, and adaptive to a variety of modalities learning-based segmentation system. In order to anticipate the final outcomes, different amounts of training data and data dimensionality (2D, 2.5D, and 3D) are used. Convolutional neural networks, or CNNs [4].

The Convolutional Neural Network (CNN) was used in this study, and it has an overall accuracy of 91.3 percent and recalls of 88 percent, 81 percent, and 99 percent in detecting meningioma, glioma, and

pituitary tumours, respectively. Deep learning architecture based on 2D convolutional neural networks for MRI image slice classification of different forms of brain tumours. Techniques such as data collecting, data pre-processing, pre-modelling, model optimization, and hyper parameter tweaking are used in this article. Furthermore, the model's generalizability was tested using 10-fold cross validation on the entire dataset [5].

III. PROPOSED METHODOLOGY:

The data was obtained from the Kaggle website. MRI pictures of a brain tumour are included in this dataset. There are two folders, one containing normal brain scans and the other containing tumour images. Both of these folders include a total of 3000 photos. Fig 1 depicts an example image of a normal brain and a brain tumour. There are 1500 tumorous and non-tumorous photos in total. The photographs are of various shapes (e.g., 630X630, 225X225), and they are shrunk to 256x256 pixels. There are 2472 photos for training, 328 for validation, and 207 for testing. There are 877 tumour photos and 795 non-tumour images among the 2472 training images. 92 tumour and 94 non tumour images obtained from 328 validation images. 116 tumour images and 91 non tumour images are detected among 207 testing images.

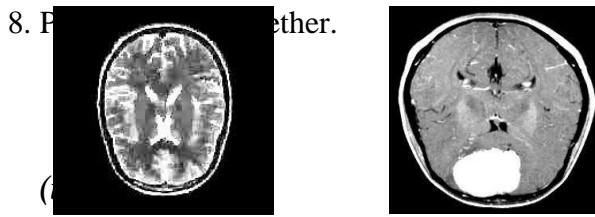


Fig:1 Tumor Negative(i) Tumor Positive(ii)

MATERIALS AND METHODS:

The two methodologies of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) are applied to the brain tumour dataset and their performance in categorising the image is evaluated.

The following are the steps involved in applying ANN on the brain tumour dataset:

1. Import the required packages
2. Open the data folder and import it.
3. Read the images, assign labels to them (for example, set Image with Brain Tumour to 1 and Image without Brain Tumour to 0), and save them in the Data Frame.
4. Change the image size to 256x256 by reading each image one at a time.
5. Make the image normal.
6. Divide the data set into three sections: training, validation, and testing.
7. Building the model

9. Put the model to the test on the train set.

There are seven layers in the ANN model utilised here. The flatten layer is the first layer, and it turns 256x256x3 pictures into a single-dimensional array. The next five levels are dense layers, with relu as the activation function and 128,256,512,256, and 128 neurons in each layer, respectively. These five layers are active because the hidden levels are hidden, and the last dense layer with a sigmoid activation function is the output layer, which has one neuron representing each of the two classes. The binary crossentropy loss function and the Adam optimization technique are used to compile the model. The training images and hence the validation images are used to create and train the model. The model is then tested using the test image set after it has been trained. Next the same dataset is given to the CNN technique.

The following are the steps involved in applying CNN on the brain tumour dataset:

1. Import the required packages
2. Open the data folder and import it (Yes and No)
3. Assign image labels to the appropriate classes (1 for Brain Tumour and 0 for No Brain Tumour)

4. Assemble the photos into a form (256X256)
5. Make the image normal.
6. Separate the photos into three sets: train, validation, and test.
7. Create the sequential model in step
8. Put the model together.
9. Use it with the train dataset (use validation set to evaluate the training performance).
10. Use the test images to evaluate the model.
11. Create a graph that compares training and validation accuracy.
12. Create a confusion matrix that compares the actual output to the projected output.

IV. OVERVIEW OF CONVENTIONAL NEURAL NETWORK:

Different layers are used to create the CNN sequential model. The original image is resized to 256x256 pixels. The convolve layer is applied to the input image with relu as the activation function and padding equal to the input picture, resulting in output images that are identical to the input image. The number of filters for distinct convolve layers is 32,32,64,128,256. With 20% of droupout, max pooling is used with a 2x2 window size and the droupout function is called. To turn

the characteristics into a one-dimensional array, the flatten method is used. The dense approach is used to create the completely connected layer, with 256 units and relu as the activation function. The output layer has one unit for each of the two classes, as well as a sigmoid as an activation function. Fig 2 depicts the Training and Testing Phase's design. The implementation is carried out in the Python programming language.

Algorithm for CNN based Classification

- Convolution filter is applied in the first layer
- The sensitivity of the filter is lowered by smoothing the convolution filter (i.e., subsampling)
- The activation layer is in charge of signal transfer from one layer to the next.
- Using a rectified linear unit can shorten the training period (RELU)
- Every neuron in the preceding layer is coupled to every neuron in the following layer.
- A loss layer is added at the conclusion of the training process to provide feedback to the neural network.

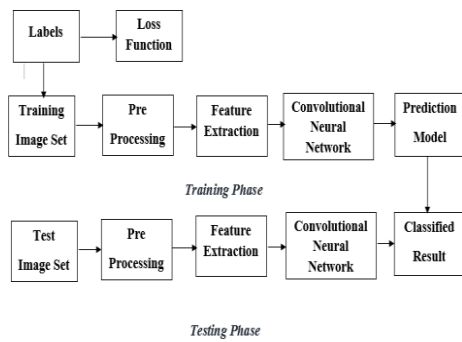


Fig:2 Training and Testing Phase

V. FRONT-END PROCESS:

DJANGO was used to design the front-end of the web application. DJANGO is a Python-based web framework for quickly building effective online apps. Django is often known as the "batteries included framework" because it has built-in features for everything, such as the Django Admin Interface and the default database, SQLite3.

The workflow will be similar to that of uploading an MRI. The user obtains the prognosis shown in Fig 3 after the model has loaded the data. The user will import a brain scan image, which will then be delivered as a http request to the model's endpoint in Fig 4. The model will send the user a response with the diagnostic.

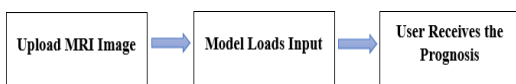


Fig:3 Django Process

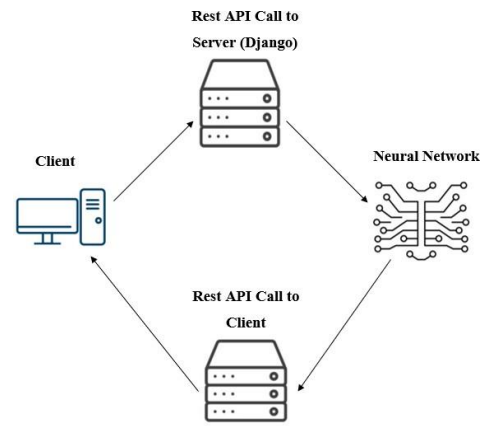


Fig:4 Client Server Framework

VI. MODEL AND TRAINING:

The model consists of:

- CNN Layer
- Average Pooling Layer
- Dense Layer
- Fully Connected Layer
- Loss Function: Categorical Cross-Entropy
 - Optimization Algorithm:

Adam Model is trained on 25 epochs.

Table:1

Models	Accuracy	Loss
Transfer Learning	97%	13%
No Transfer Learning	76%	49%

TRANSFER LEARNING: MODEL ACCURACY, LOSS CURVE

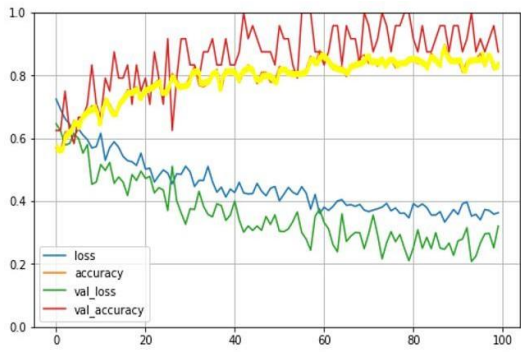


Fig:5 Accuracy Graph

VII.EXPERIMENTAL RESULT

ANALYSIS:

The image data is stored in the data variable, which is of the array datatype. The class labels for the photos are also generated and stored in the array variable data target. After that, the photos are inserted into the dataframe. The image dataset is split into three sections: training, validation, and testing. The accuracy and loss acquired when the ANN model is applied to the training and validation datasets are shown in Fig 5. When the ANN model is run for fifty epochs on the training data, the training accuracy is 97.13 percent and the validation accuracy is 71.51 percent. When applied to the testing data, it yields an accuracy of 80.77 percent. Python is used to carry out the simulation.

The precision is calculated and compared to other state-of-the-art approaches. To determine the efficiency of the proposed brain tumour classification system, the

training accuracy, validation accuracy, and validation loss are determined. Support Vector Machine (SVM)-based categorization is used in the current technique to detect brain tumours. It necessitates the output of feature extraction. The classification output is generated and accuracy is calculated based on feature value. In SVM-based tumour and non-tumour identification, the computation time is long and the accuracy is low. The suggested CNN-based classification does not necessitate separate feature extraction methods. CNN is used to calculate the feature value. Fig 6 depicts the Tumour and Non-tumour brain imaging classification results. As a result, the complexity and computing time are minimal, yet the accuracy is great. Fig 7 shows the accuracy of brain tumour classification. Finally, depending on the probability score value, the categorization results in Tumour brain or non-tumour brain.

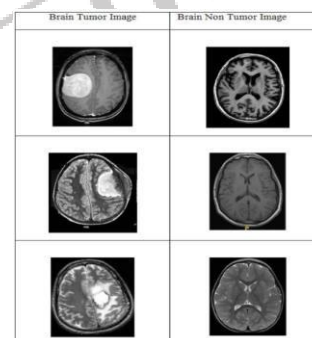


Fig:6 Tumor and Non-Tumor Images

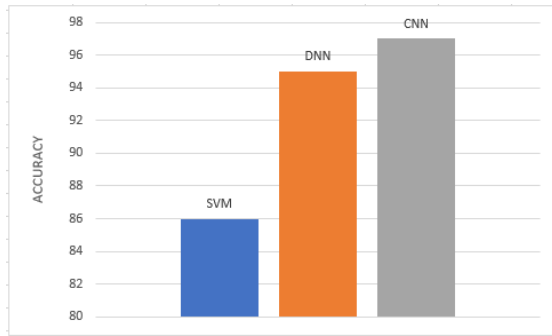


Fig:7 Comparison Graph

VII. CONCLUSION:

The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. In the conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction and SVM and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low. Further to improve the accuracy and to reduce the computation time, a convolution neural network-based classification is introduced in the proposed scheme. Also, the classification results are given as tumor or normal brain images. CNN is one of the deep learning methods, which contains sequence of feed forward layers. Also, python language is used for implementation. Image net database is used for classification. It is one of the pre-trained models. So, the training is performed for only final layer. Also, raw pixel value with

depth, width and height feature value are extracted from CNN. Finally, the Gradient decent based loss function is applied to achieve high accuracy. The training accuracy, validation accuracy and validation loss are calculated. The training accuracy is 97.5%. Similarly, the validation accuracy is high and validation loss is very low.

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