An Approach to Detect the Presence of Neoplasm with Convolutional Neural Network

Nikunj Mahesh Wadgeri
Dept. of CSE
Vignana Bharathi Institute of Technology, Hyderabad

Dr. Raju Dara
Associate Professor, Dept. of CSE
Vignana Bharathi Institute of Technology, Hyderabad

Abstract:- The human brain is the nervous system's command centre, governing functions such as memory, vision, hearing, knowledge, personality, problem-solving capabilities, and so on. Deep learning has gained traction in almost every field where decision-making is crucial. Machine learning and deep learning algorithms in healthcare have exhibited promising results in a variety of sectors, like cancer detection with Magnetic Resonance Imaging (MRI), surgical robots, and so on. Deep learning is being employed to detect the presence of neoplasms in scanned MRI images. Neoplasm is characterized as the uncontrolled proliferation of tissues in a specificportion of the body, notably those with cancer-like traits. A brain tumour is a category of neoplasm generated by development of abnormal brain cells. Non-cancerous (benign) tumours and cancerous (malignant) tumours are the two main types of brain tumours. In accordance with the study, age plays a role in overall lifeexpectancies when a brain tumour is diagnosed. The 5-year survivalrate for people under the age of 15 is anticipated to be approximately 75%. The 5-year survival rate for people aged 15 to 39 is anticipatedto be approximately 72%. The 5-year survival rate for persons aged40 and up is expected to be around 21%. Treatment for brain tumours is governed by several parameters, including that of the form of cancer, the abnormalities of the cells, and the location of the cancer in the brain. It is simple to anticipate and diagnose brain tumours at an early stage using Artificial Intelligence. Deep learning models are used to diagnose brain tumours by analysing MRI scan data. Convolutional Neural Networks (CNN) as well as other deep learning models can be used to detect tumours in scanned brain images.

Keywords:- *Human Brain, MRI, Neoplasm, Deep Learning, Convolutional Neural Network.*

I. INTRODUCTION

Today, we live in an era where illnesses are on the rise, necessitating the advancement of treatment quality. Tumours are irregular bulges that can appear anywhere on the body and are one of the most hazardous illnesses. The most dangerous ofall cancers is a brain tumour, which can develop in any area of the brain. It is primarily described as aberrant cell proliferation in the brain. These aberrant cells can cause damage to healthy brain cells, resulting in brain dysfunction. There are several distinct forms of brain tumours. These tumours can be either malignant (cancerous) or benign (not cancerous).

CNN outperforms the competition due to its widespread application in image recognition. It is essentially a collection of neurons with weights that may be learned. They are also noted for their exceptional precision and performance. Because of the noise and abnormalities in the picture, human observation in predicting the tumour might be misleading. This drives our efforts to develop a tumour prediction algorithm. This contains methods for identifying tumours. As this is a basic introduction to neural networks such as CNN, artificial neural networks will be used to briefly discussed in order to truly comprehend the CNNs. Inputs stream into a hidden layer with distortions or weightings and outputs alter as the system 'learns' from a dataset to achieve the desired conclusion in artificial neural networks.

One of the applications of convolutional neural networks is predicting low-grade tumours and high-grade tumours—also known as brain tumours as an example of the machine learning application. Convolutional neural networks (CNNs) is indeed avariety of deep learning structure based on the optical cortex ofhumans and is commonly utilized for tumour prediction. Gradient descent is applied to calculate the loss function. Through a score function, raw image pixels are mapped to class scores. Loss functions are used to measure the quality of a particular set of parameters. Using the training data, it is determined whether the induced scores agree with the ground truth labels. Calculating the loss function is very helpful to improve accuracy. If the loss function is high, accuracy is low. Similarly, accuracy is high, when the loss function is low. To compute the gradient descent algorithm, the gradient value is calculated for the loss function. A convolution neural network is used to detect brain tumours efficiently and accurately. Using the Python programming language, simulations are carried out. In this project, accuracy is calculated and compared to all other state-of-the-art methods. Training accuracy, validation accuracy, and validation loss are calculated to assess the efficiency of the proposed brain tumour classification system. As a classification approach for identifying brain tumours, Support Vector Machine is recommended. It demands the outcome of feature extraction. A classification output is generated and indeed the accuracy is computed using the feature values. In SVM-based tumour and non-tumour detection, computation time is substantial and the accuracy is low. Deep Neural Network (CNN) takes on a different approach, replicating how our eyes aid us in comprehending our environment. When we see a picture, we automatically divide it into a range of smaller sub-images and analyse each one separately followed by analysing and interpreting the image by merging these sub-images altogether. Here the question arises, what is the best way to apply this approach in a convolutional neural network?

The work is completed in the so-called convolution layer. To do this, create a filter that specifies how large the partial pictures are examined, as well as a step length that defines howmany pixels are available between computation, or how adjacent the partial images are to one another. This approach greatly reduces the dimensionality of image. The next layer is the pooling layer. From a purely computational standpoint, thesame thing happens here that it does in the convolution layer, with the exception that according to the application, we only extract the average or maximum value from the output. This saves minute details in a few pixels that are essential to the task's accomplishment. The fully-connected layer, that we are familiar with it from classic neural networks, is the last layer. Next is to use the densely meshed layers now that have significantly shrunk the image's dimensions. To recognize the links and complete the categorization, the various sub-images are linked once again in this scenario.

II. RELATED STUDY

P. Natarajan et al., [1] shows how image processing is used toextract brain tumours from MRI brain images. The exact location of a brain tumour cannot be determined by MRI images. Using image segmentation, this shows the precise shape of the tumour in that MRI image but is unable to indicate the presence of tumours at an early stage.

Maiti et al., [2], MATLAB platform is used to run the developed method. The brain MRI pictures always segmented to remove the tumour. As the HSV colour space contains more information than the grey image, it is discovered in this work that when this developed method is applied to a grey image to segment the tumour region, the performance is not as good as that obtained in the colour model. Since the majority of MRI scans are black and white, utilizing the aforementioned method will not yield good accuracy; however, when compared to this method, employing CNN will yield the highest accuracy.

Parveen et al., [3], demonstrated how the Fuzzy C-Means segmentation approach is used to classify tumour and non- tumour areas in the brain This method is in contrast to a classification technique known as Linear Discriminant Analysis (LDA) and Radial Basis Optimisation. The performance is quite poor, and the intricacy is quite high.

S. S. Hunnur et al., [4], discussed the thresholding method fordetecting brain tumours The size and stage of the tumour are mentioned. MRI is the most effective imaging method for identifying brain tumours. Brain tumour identification utilisingMRI scans is employed in this work, along with digital image processing methods. The disadvantage of this approach is that it cannot be used with MRI pictures of varying sizes or pixel density.

N. Kaur et al., [5] When there are clusters of wide variations and size, k-means has challenges in clustering the data. By grouping a few of the anomalies into a distinct cluster, K-means erroneously utilised. Even in the instance of a brain tumour, where all the clusters are spherical, have identical radii, and arewell-separated, the k - means clustering algorithm fail to give the most accurate result in predicting the brain tumour.

D. Divyamary et al., [6] The Naïve Bayes classifier was proposed as the simplest method for identifying tumour. It merely requires a smaller number of training data sets. As, only a few images are required for the Naïve Bayes classifier hence, we cannot implement the same model for our dataset consisting of more than 3000 images. In the above method only if the images are having brain tumour or not is mentioned, there is no work done in predicting the percentage accuracy of brain tumour spread across the brain.

Ming-Ni & Lin et al., [7] suggested the use histogram equalisation. This technique for adjusting contrast is excellent for photographs where the foreground and background are equally dark. It uses histogram equalisation to improve contrast. Contrast does not necessarily need to be increased in this. Therefore, this approach is ineffective for finding tumours.

III. DATASET CHARACTERISTICS

The public Kaggle database is utilized to collect the MRI scansnecessary for brain tumour identification. The Kaggle databaseincludes a variety of numerous distinct disease-related images that can be used for analysis and research. The relevant MRI data is in picture (.img) format. Three thousand photos total, split into two halves. 1500 photographs make up the first section, which includes a batch of images with a brain tumour, and 1500 images make up the second part, which does not. Every image of the dataset is unique, no two similar images are present in the dataset. Each of the images varies in pixels and size.

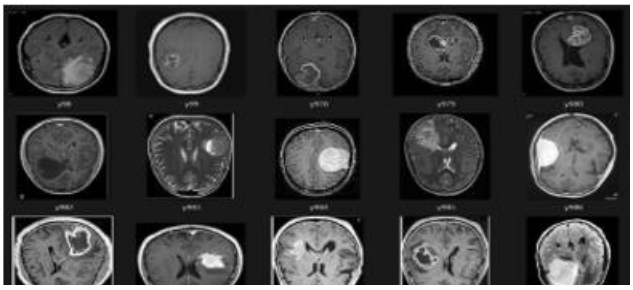


Fig. 1. 15 slices of MRI images having a brain tumour

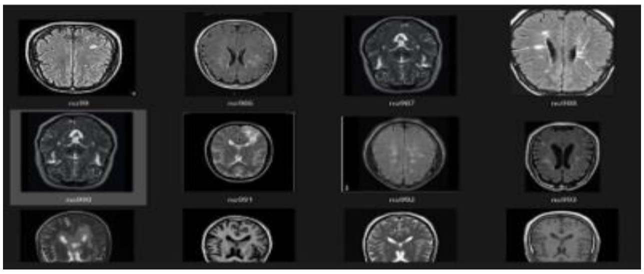


Fig. 2. 12 slices of MRI images not having a brain tumour

IV. PROPOSED SYSTEM

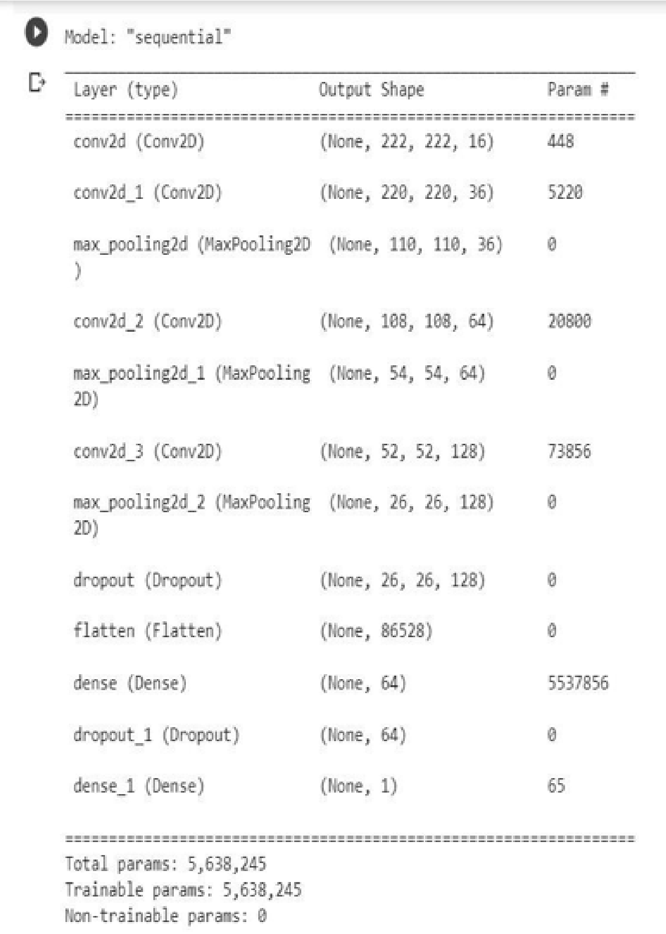
The human brain is primarily made up of three parts: the cerebrum, which is the largest portion of the brain, the cerebellum, which is situated beneath the cerebrum, and the brain stem, which joins the cerebrum, cerebellum, and spinal cord together. Each of the right and left hemispheres of the cerebrum, which is made up of grey matter, white matter, and cerebrospinal fluid, is divided into two halves. A brain MRI slice's spatial variation of the grayscale intensities is caused by different tissue types being compressed to form fissures and folds in a compact way. Each hemisphere of the cerebrum has four lobes, which are separated by fissures and folds. Any area of the brain can develop a brain tumour, and it can have any shape. Therefore, fluctuations in intensity in the brain MRI is by the presence of the tumour. In MRI, tumour-affected areas typically exhibit pixels with a larger intensity range than their surrounding pixels. In order to make predictions about whethera brain tumour is present or not, the proposed method aims to determine by what percentage the intensity of pixels in an MRIslice changes. To do this, the photos in the dataset have been separated into three groups, with 80% of the images remainingin the folder used for training and developing our CNN model for the predictions. The remaining 20% of the photos are split into testing and validation folders, each containing 10% of the total images left. It will utilize the images of the testing folder to test and predict the presence of brain tumours with our CNNmodel along with its accuracy.

A. Algorithm for CNN-based Classification

- In the first layer, use a convolution filter.
- The next step is to smoothing theconvolutional filter that reduces the filter's sensitivity.
- The activation layer is used which governs the signal transmission from one neuron to the next.
- Reduce the training period by implementing a rectified linear unit (RELU)
- Every neuron in the previous layers is connected to every perceptron.
- At the end of the training, a loss layer is included to provide feedback to the neural network.

B. Building a Convolutional Neural Network

- By specifying the order of each layer in TensorFlow, construct the convolutional neural network.
- employ the stack of Convolutional Layer andMax Pooling Layer twice since we are dealing with images. The images have 224 height dimensions, 224 width dimensions,and 3 colour channels, as is already known (red, green, and blue).
- The Max Pooling Layer looks for the highestvalue within a 2x2 matrix while the Convolutional Layer employs 16 filters initially, 36 filters later, and so on up to 128filters with a 3x3 kernel as a filter.



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 16)      448

 conv2d_1 (Conv2D)           (None, 220, 220, 36)      5220

 max_pooling2d (MaxPooling2D  (None, 110, 110, 36)     0
 )

 conv2d_2 (Conv2D)           (None, 108, 108, 64)      20800

 max_pooling2d_1 (MaxPooling  (None, 54, 54, 64)       0
 2D)

 conv2d_3 (Conv2D)           (None, 52, 52, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 26, 26, 128)      0
 2D)

 dropout (Dropout)           (None, 26, 26, 128)       0

 flatten (Flatten)           (None, 86528)             0

 dense (Dense)               (None, 64)                5537856

 dropout_1 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

=================================================================
Total params: 5,638,245
Trainable params: 5,638,245
Non-trainable params: 0
```

Fig. 3. Parameters of the trained CNN model

- The model with a total of 5,638,245 parameters is now ready to be built and trained.
- The model must first be compiled before it can begin training the convolutional neural network. For that, we specify the optimizer,or method that determines how the parameters change (the Adam
- algorithm) and the metric (accuracy) thatwill be displayed to allow us to track the training process.

V. RESULTS AND DISCUSSION

The accuracy of the model has remained at 84.959% from epoch 13, even after training the convolutional neural network for a total of 19 iterations. The model has now been stored with the.h5 extension, and it will now be used to predict brain tumours from the testing and validation folder that are produced in earlier steps. To better understand how the Sequential (CNN) model performed during the training cycle, the Loss v/s Accuracy graph was plotted. Finally, predictions are made on the MRI scans regarding the presence or absence of a brain tumour using the model. The "red" line indicates the Accuracy and the "yellow" line indicates the Loss.

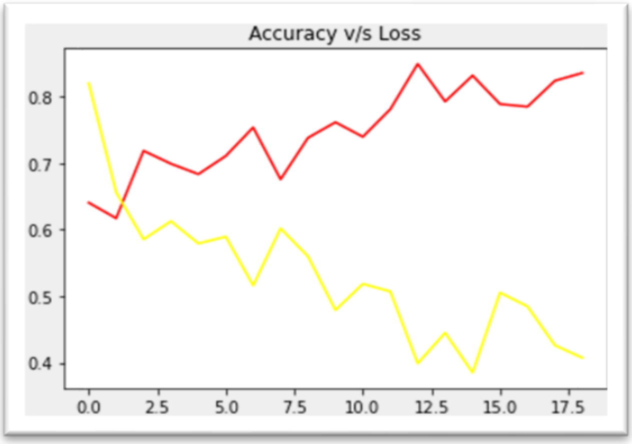
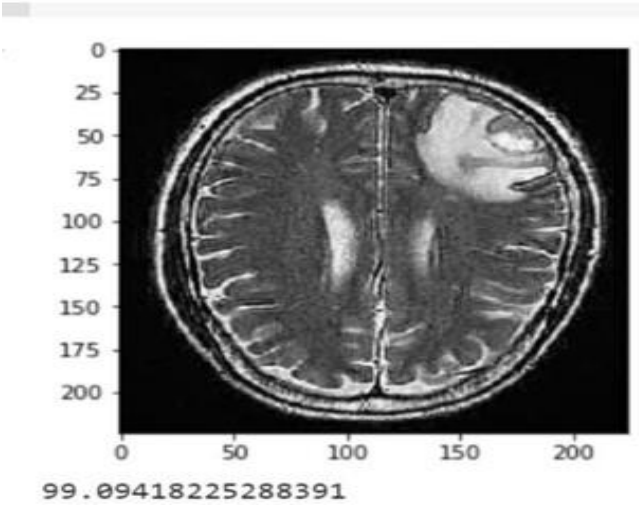


Fig. 4. The Loss v/s Accuracy graph



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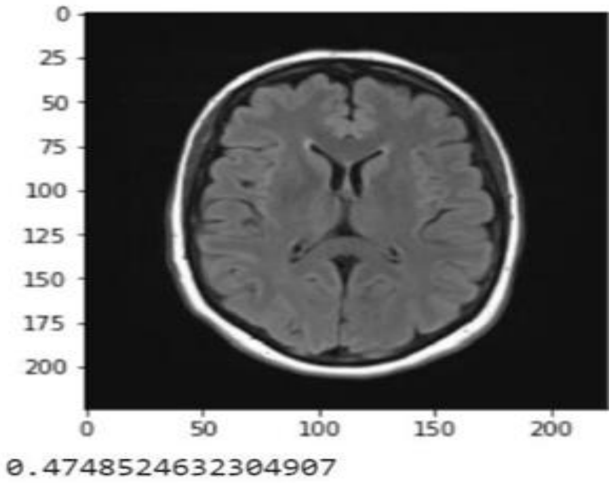
99.09418225288391
```

Fig. 5. Image predicting active presence of brain tumor.



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0.4748524632304907
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Fig. 6. Image predicting absence of brain tumor.

VI. CONCLUSION

We can infer from the above result that the constructed model has an 84.959% chance of correctly predicting the change in pixel intensity in brain MRI image. As a result of this research, it was concluded, if the number is less than 05.00, it indicates the absence of a brain tumor, and if it is greater than 95.00, it indicates the presence of a brain tumor.

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