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BRAIN TUMOR DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Brain tumor is one of the most complicated diseases to treat in modern medicine. In the early stages of tumor development, the radiologist's primary concern is often an accurate and efficient study. Due to cancer large no of patients are in danger. The medical field needs fast, automated, efficient and reliable technique to detect tumor like brain tumor. Detection plays very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming.

Image processing is the one of the most demanding and promising field nowadays. Tumor is a abnormal growth of cell in human brain. The tumor can be categorized as benign(non-cancerous) and malignant(cancerous). Earlier stage of tumor is used to be detected manually through observation of image by doctors and it takes more time and sometimes gets inaccurate results. Today different automated tools are used in medical field. These tools provide a quick and precise result. Magnetic Resonance Images (MRI) is the most widely used imaging technique for analyzing internal structure of human body. The MRI is used even in diagnosis of most severe disease of medical science like brain tumors. The brain tumor detection process consist of image processing techniques involves four stages. Image pre-processing, image segmentation, feature extraction, and finally classification. There are several existing of techniques are available for brain tumor segmentation and classification to detect the brain tumor. There are many techniques available presents a study of existing techniques for brain tumor detection and their advantages and limitations. To overcome these drawbacks, propose a Convolution Neural Network (CNN) based classifier. CNN based classifier used to compare the trained and test data, from this get the best result.

Keywords: brain tumor; deep learning; convolutional neural network (CNN)

I.INTRODUCTION

A brain tumor is an abnormal growth or mass of cells in or around the brain. It is also called a Central Nervous System Tumor. Brain tumors can be malignant (cancerous) or benign (not cancerous), Some tumors grow quickly, others are slow growing. Tumor in the brain can seriously disrupt the central nervous system. Furthermore, the mass of tumor-cells can affect the brain's regular functionalities. It should also be noted that many types of tumors make the brain tissue subjected to a scaling-up occurring over time, which leads to brain cells damage.

The cause of brain tumors is exposure to large amounts of radiation from X-rays or earlier cancer treatment. Some brain tumors occur when hereditary conditions are passed down among family members and symptoms of a brain tumor vary depending on the tumor's location and type, size and what the affected part of the brain controls. It is observed that brain tumors occur more often in men than women.

Although they are most common among older adults, they can develop at any age. However, early discovery of brain tumors helps significantly improve the possibility of treatment and survival rate of the patients. In spite of this, manual classification of tumor using a significant quantity of MRI scans, generated in clinical routine, is time and labor consuming task. In fact, the use of the magnetic resonance imaging (MRI) technique in medicine produces high quality images. This kind of imaging is often used by scientists in detecting brain tumors and showing their progress over time.

MRI images play a crucial role in automatic medical analysis field as they facilitate visualizing the different brain structure, thus providing detailed information about it. Scientists have developed different techniques for detecting and classifying brain tumors using MRI images. These approaches range from classical medical image processing to advanced machine learning techniques.

Deep learning is a machine learning technique that teaches computers to do what comes naturally to humans like learn by example. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction. In ML Algorithms everything is flattened and in single dimension array while in deep learning something called a tensor. It has basically small matrices inside a big matrix, so it can be considered as matrix nested inside a matrix.

Brain tumor is one of the vital organs in the human body, which consists of billions of cells. The abnormal group of cell is formed from the uncontrolled division of cells, which is also called as tumor. Brain tumor are divided into two types such low grade (grade1 and grade2) and high grade (grade3 and grade4) tumor. Low grade brain tumor is called as benign. Similarly, the high grade tumor is also called as malignant. Benign tumor is not cancerous tumor. Hence it doesn't spread other parts of the brains. However the malignant tumor is a cancerous tumor. So it spreads rapidly with indefinite boundaries to other region of the body easily. It leads to immediate death.

Brain MRI image is mainly used to detect the tumor and tumor progress modeling process. This information is mainly used for tumor detection and treatment processes.MRI image gives more information about givenmedical image than the CT or ultrasound image. MRI image provides detailed information about brain structureand anomaly detection in brain tissue.Actually, Scholars offered unlike automated methods for brain tumors finding and typecataloging using brain MRI images from the time when it became possible to scan and freight medical imagesto the computer. Conversely, Neural Networks (NN) and Support Vector Machine (SVM) are theusually used methods for their good enactment over the most recent few years. However freshly, Deep Learning (DL) models fixed a stirring trend in machine learning as the subterranean architecturecan efficiently represent complex relationships without needing a large number of nodes likein the superficial architectures e.g. K-Nearest Neighbor (KNN)and Support Vector Machine (SVM).Consequently, theygrew quickly to become the state of the art in unlike health informatics areas for examplemedical image analysis, medical informatics andbioinformatics

1.1. Classification of Tumour

There are three basic types of tumours: 1) Benign; 2) Pre-Malignant; 3) Malignant (cancer can only be malignant)

1.1.1. Benign Tumour

A Benign Tumour is not always Malignant or cancerous. It might not invade close tissue or unfold to alternative components of the body the way cancer can. In most cases, the outlook with benign tumours is not at all serious but it can be serious if it presses on vital structures such as blood vessels or nerves.

1.1.2. Pre-Malignant Tumour

In these tumours, the cells are not cancerous. However, they need the potential to become malignant. The cells will grow and unfold to alternative components of the body.

1.1.3. Malignant Tumour

Malignancy (mal- = "bad" and ignis = "fire") Malignant tumours area are cancerous. They develop once cells grow uncontrollably. If the cells

still grow and unfold, the malady will become dangerous. Malignant tumours will grow quickly and unfold to alternative components of the body during a method known as metastasis.
A latest research in the year 2021 says that in United States among 24530 adults (13840 men

& 10690 Women) will be identified with cancerous tumours of brain and in the spinal cord. A person's probability of developing this type of brain tumour in their lifespan is less than 1%. It causes 85% to 90% of all primary central nervous system (CNS) tumours. A number of 3,460 children under the age of 15 will also be identified with a brain or CNS tumour this year, other than this deals with adult primary brain tumours. Brain and alternative system nervous cancer is the tenth leading reason behind death for men and women. It is evaluated that 18,600 adults (10,500 men & 8,100 women) may die from primary cancerous brain and CNS tumours in the year 2021. Hence it's important to improve the accuracy of previously proposed methods for the betterment of medical image research. In our project, our proposed CNN-based algorithm is 90.74% accurate, it will help medical representatives in their treatment job without manually analyzing the MRI images so that the treatment speed can be enhanced.

1.2 Deep Learning (DL)

Deep learning is a specialized form of machine laming. A machine learning workflow starts with relevant features being manually extracted from images. The features are then used to create a model that categorizes the objects in the image. With a deep learning workflow, relevant features are automatically extracted from images. In addition, deep learning is performed end-to-end where a network is given raw data and a task to perform, such as classification, and it learns how to do this automatically.

A key advantage of deep learning networks is that they often continue to improve as the size of your data increases. Deep learning has been applied in many applications, such as pattern classification object detection, speech recognition and other decision-making tasks. However, the main challenge for DL is the huge amount of data necessary for training.

Deep learning can be considered as a subset of machine learning. It is a field that is based on learning and improving on its own by examining computer algorithms. While machine learning uses simpler concepts, deep learning works with artificial neural networks, which are designed to imitate how humans think and learn. Until recently, neural networks were limited by computing power and thus were limited in complexity. However, advancements in Big Data analytics have permitted larger, sophisticated neural networks, allowing computers to observe, learn, and react to complex situations faster than humans.

Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention.

Artificial neural networks, comprising many layers, drive deep learning. Deep Neural Networks (DNNs) are such types of networks where each layer can perform complex operations such as representation and abstraction that make sense of images, sound, and text. Considered the fastest-growing field in machine learning, deep learning represents a truly disruptive digital technology, and it is being used by increasingly more companies to create new business models. Now, as you have understood what is Deep Learning, let's begin to understand how does Deep Learning works.

1.3. PROBLEM STATEMENT

A. Motivation

Diagnosing tumors in medical imaging is time consuming due to its manual nature as it mainly relies on human ability and judgment. Specialists in this field, such as radiologists, examine images from CT scans, MRIs, and PET scans and make decisions on which treatment depends. This assiduous process takes a couple of hours to complete. Automation of the detection process helps to cut down a significant amount of time and effort needed.

B. Objective

The primary goal of this work is to create a model that can predict whether or not MRI images include cancer. We created and trained a model that could detect the tumor, presenting an efficient and

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effective way for assisting in the segmentation and identification of brain tumors that eliminates the need for manual labor. Finally, when we compared the outcomes of all tests, we discovered that certain models performed better in terms of accuracy and loss metrics.

1.4 EXISTING SYSTEM

MRI, also known as Magnetic Resonance Imaging, is mostly used for brain tumor or lesion detection. Brain tumor segmentation from MRI is one of the most crucial tasks in medical image processing as it generally involves a considerable amount of data. Moreover, tumors can be ill-defined with soft tissue boundaries. So, it is a very extensive task to obtain the exact segmentation of tumors from the human brain.

The large-scale manual examination method can often lead to misinterpretation due to some factors such as fatigue and excessive abundance of MRI slices. In addition, it is non-repeatable and results in intra- and inter-reader variability. Alleviating these concerns requires developing a detection system method to diagnose various brain abnormalities.

1.5 PROPOSED SYSTEM

The human brain is modeled by using design and implementation of neural network. The neural network is mainly used for vector quantization, approximation, data clustering, pattern matching, optimization functions and classification techniques. The neural network is divided into three types based on their interconnections.Three type neural networks are feedback, feed forward and recurrent network. The Feed Forward Neural network is further divided into single layer network and multilayer network. In the single layer network, the hidden layer is not presented. But it contains only input and output layer. However, the multilayer consists of input layer, hidden layer and output layer. The closed loop based feedback network is called as recurrent network.

In the normal neural network, image cannot scalable. But in convolution neural network, image can scalable (i.e) it will take 3D input volume to 3D output volume (length, width, height).The Convolution Neural Network (CNN) consists of input layer, convolution layer, Rectified Linear Unit (ReLU) layer, pooling layer and fully connected layer. In the convolution layer, the given input image is separated into various small regions. Element wise activation function is carried out in ReLU layer. Pooling layer is optional. We can use or skip. However the pooling layer ismainly used for down sampling. In the final layer (i.e) fully connected layer is used to generate the class score or label score value based on the probability in-between 0 to 1.

We proposed an efficient and skillful method which helps in the segmentation and detection of the brain tumor without any human aid based on Convolutional Neural Network. It aims to classify brain MRI images into two classes, images with tumor and images without tumor or healthy.

First, different pre-processing steps are applied to the MRI images for image augmentation and enhancement. The original dataset consists of MRI images from which some of them are having tumor and some of them are non-tumorous. The datasets are further split into train, validation, and test sets. The pre-trained CNN architectures are used to test and evaluate the proposed model.

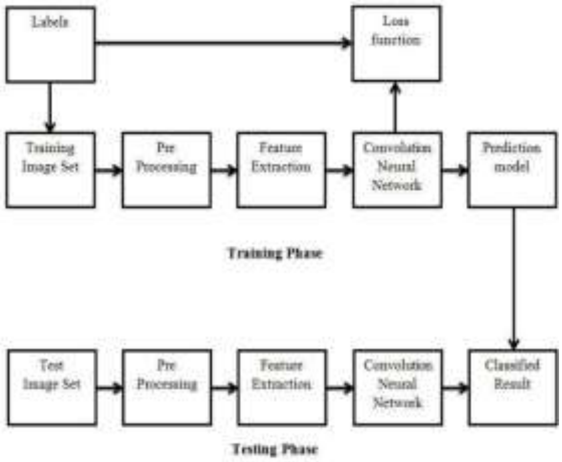

Figure 1 Block Diagram of Proposed Brain Tumor Classification Using CNN

The block diagram of brain tumor classification based on convolution neural network is shown in figure.1.1. The CNN based brain tumor classification is divided into two phases such as training and testing phases. The number of images is divided into different category by using labels name such as tumor and non-tumor brain image…etc. In the training phase, preprocessing, feature exaction and classification with Loss function is performed to make a prediction model.

Initially, label the training image set. In the preprocessing image resizing is applied to change size of the image.

Finally, the convolution neural network is used for automatic brain tumor classification. The brain image dataset is taken from image net. Image net is a one of the pre-trained model. If you want to train from the starting layer, we have to train the entire layer (i.e) up to ending layer. So time consumption is very high. It will affect the performance. To avoid this kind of problem, pre-trained model based brain dataset is used for classification steps. In the proposed CNN, we will train only last layer in python implementation. We don't want to train all the layers. So computation time is low meanwhile the performance is high in the proposed automatic brain tumor classification scheme.

The loss function is calculated by using gradient descent algorithm. The raw imagepixel is mapping with class scores by using a score function. The quality of particular set of parameters is measured by loss function. It is based on how well the induced scores approved with the ground truth labels in the training data. The loss function calculation is very important to improve the accuracy. If the loss function is high, when the accuracy is low. Similarly, the accuracy is high, when the loss function is low. The gradient value is calculated for loss function to compute gradient descent algorithm. Repeatly evaluate the gradient value to compute the gradient of loss function.

II.LITERATURE SURVEY

The topic of medical image processing has seen a lot of diverse work done recently. The topic of medical image processing is now home to scientists from a variety of disciplines, such as computer vision and machine learning. Consequently, we examined some of the studies conducted to determine the most efficient and advanced techniques that might be significant for us.

Devkota et al. [1] developed the complete segmentation process on the basis of Mathematical Morphological Operations and the spatial FCM technique, which decreases computational effort, although the suggested solution has not been tested to the assessment stage. It identifies malignancy with 92% accuracy and labels it with 86.6% accuracy.

In the study by Dr. Chinta Someswararao et al. [2] , where he used a combined Convolution neural network classifier model for determining whether or not the patient has a brain tumor along with machine vision to automatically crop the patient's brain from MRI scans. His overall accuracy is much higher than, say, the criterion of 50%. However, it might be significantly enhanced by using more train data or alternative models and approaches. By combining a clever edge detection technique with adaptive thresholding, Badran et al. [3] were able to extract the ROI. The dataset contained 102 images. A Canny algorithm for edge detection and adaptive thresholding were applied to the initial and next following set of the neural network respectively after the images had been preprocessed.

The removal of brain tumors was made simple, fully automated, and effective by Khurram Shahzad and Imran Siddique et al. [4]. The use of morphological gradients and thresholds, as well as morphological operations like erosion and dilation, is made. The morphological gradient is used to calculate the threshold. When the image is converted to black and white using threshold, a tumor and some noise appear on the screen. By compressing the image and employing erosion techniques to reduce noise or unwanted little elements, the image is thinned. Following erosion, dilation is used to rebuild the portion of the removed tumor that erosion has destroyed.

III.METHODOLOGY

3.1 Data Preprocessing

Preprocessing is the term used for all the steps taken to enhance the dataset in preparation for analysis. The images from the dataset have been skull-tripped and co-registered. The tumor segmentation labels have been produced by an automated hybrid generative method. These segmentation labels have been manually corrected by a board-certified Neuroradiologist. The final images have rich imaging features, including intensity, volumetric, morphological, histogram-based and textural parameters. The brain data is measured in voxels. They are analogous to the pixels used to display images on a computer screen.

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3.2 Allocating Train, Test and Validation Sets

The dataset is divided into three subsets, i.e., training set, validation set and test set. The training dataset is used to train the model . The validation set is used to fine-tune the parameters of a model that has been deduced from the training set . The validation step indirectly affects the generated model. The test set is the sample of data used to provide an unbiased evaluation of the generated model (Brownlee, 2017). Following convention, 15% of the dataset has been randomly allocated to the test set. 10% of the remaining dataset is allocated to the validation set. The remainder of the dataset is used for training the model.

Figure 2 Part of Validation Sets and Training Sets

3.3 Data Augmentation

Image data augmentation generates new training samples from the original dataset. Random alterations in the arrangement of the images are used for generating the model, whilst maintaining the class labels of the data (Gu, Pednekar and Slater et.al [13]). Generally, the common methods to incorporate variation of features are as follows:

• flip horizontally or vertically

• rotate by fixed amount

• shuffle and transform

When applying data augmentation, our goal is to increase the generalizability of the model. Data augmentation is only applied in the training phase. The test set is required to provide an unbiased evaluation of the generated model. Data augmentation can be implemented using the ImageDataGenerator method in Keras (Gulli and Pal et.al [14]). The method takes an array of images as its argument. It transforms each image in the array through a series of random transformations to achieve augmentation. Lastly, the array of augmented images is returned to the calling function.

3.4 Classification

Machine Learning is applied in two different ways — classification & regression. Classification is often used for data in the discrete domain, whereas regression is applied for data in the continuous domain. In this investigation, we hope to generate a model which predicts whether an image contains a tumor or not. This translates to a binary output which is a problem in the discrete domain. Machine Learning in the discrete domain is applied through classification.

3.4.1 Dataset

The dataset is taken from Github website. This dataset contains MRI images of brain tumor. There are two folders one represents the normal brain image and the other represents the tumor images. Totally there are 2065 images in both these folders. Totally 1085 tumorous and 980 non-tumorous images are taken. The images are of different shapes (eg.630X630,225X225) and these image are resized to 256x256.1672 images for training, 186 images for validation and 207 images for testing is taken. Out of 1672 training image, 877 images are tumor image and 795 images are non tumor image. 92 tumor and 94 non tumor images taken from 186 validation images. Among 207 testing images, 116 tumor images and 91 non tumor images.

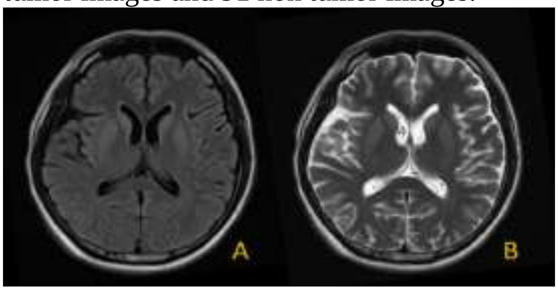

Figure 3. Brain MRI Images Dataset Sample (A) = image with dark margins, (B)= image without dark margins).

3.5 Convolution Neural Network (CNN)

A Convolution Neural Network model is used to classify the MRI Brain scans revealing whether they contain a tumor or not. CNN models are commonly used in object recognition applications ,CNNs are

comprised of three types of layers — convolutional layers, pooling layers, and fullyconnected layers. When these layers are stacked, a CNN architecture is formed.
The basic functionality of CNN can be broken down into four key areas:

1) The input layer will hold pixel values of the MRI scan of brain.

2) Convolutional Layer:

The Convolutional layer is the core block of the Convolutional Neural Network. It has some special properties. It does most of the computational heavy lifting. The CONV layer's parameters consist of a set of learn-able filters. Every filter is small spatially (along width and height), but extends through the full depth of the input volume.

For example, a typical 3X3 filter on a first layer of a ConvNet might have size 5*5*3 (i.e., 5 pixels width and height, and 3 because images have depth 3, the color channels). During the forward pass, each filter is convolved across the width and height of the input volume and dot products are computed between the entries of the filter and the input at any position. As the filters are slided over the width and height of the input volume, a 2-dimensional activation map will be produced that gives the responses of that filter at every spatial position. Intuitively, the network will learn filters that activate when they see some type of visual feature such as an edge of some orientation. These activation maps are stacked along the depth dimension and the output volume is produced.

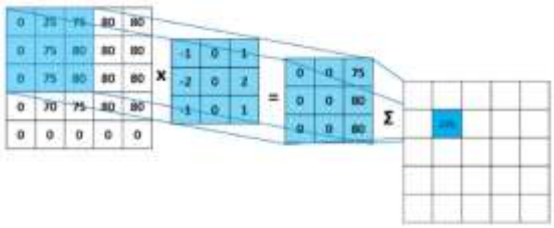

Figure 4 Convolution Operation of CNN

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

To bring down whole knowledge of requirements and analysis on the desk and design the software product. The inputs from users and information gathered in requirement gathering phase are the inputs of this step. The output of this step comes in the form of two designs: logical design and physical design. Engineers produce meta-data and data dictionaries, logical diagrams, data-flow diagrams and in some cases pseudo codes.

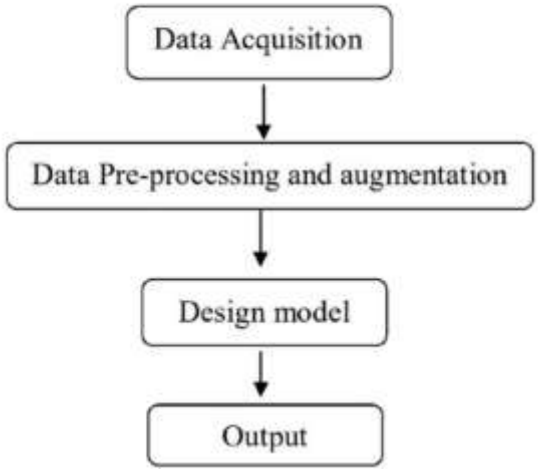

Figure 5 System Architecture Diagram

DATA ACQUISITION
The dataset used for training and testing was collected from Kaggle. It contains brain MRI images in which some of them are images containing tumor (tumorous images) and some images are normal (without tumor). Tumorous images are segregated in folder named "Yes" and normal images are kept in "No" folder. The images are in different formats and of variable sizes.
DATA PRE-PROCESSING AND AUGMENTATION
For any machine learning project data pre-processing is the most crucial and initial step. In this the raw data was collected and making it useful for machine learning model. As mentioned, the dataset contains images of different formats and sizes which may contain noise. This can lead to errors in classification and segmentation. Pre-processing the image will reduce this problem and data can be transformed in a standard format acceptable for classification and segmentation.

Deep Learning needs a large dataset for producing accurate results. Image augmentation is a process of increasing the size of the dataset by producing copies of images through different ways of processing like random rotation, shifts, shear, and flips by using the Image Data Generator tool in

Keras TensorFlow. This process boosts the model to generalize better and helps prevent overfitting.

DESIGN MODEL
We are using CNN, transfer learning and its architecture called Mobilenet to design our model which is used to improve the accuracy of our model. Before training our model, the whole dataset was divided into three parts called Training, Testing and Validation Dataset. Training data is used to train the model and Testing data and Validation data was used to test the model. In this project 70% of the data was taken as training data and 15% was taken as testing data as well as validation data.

DEPLOYMENT
The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system. If the above-prepared model is producing an accurate result as per our requirement with acceptable speed, then we deploy the model in the real system. The deployment phase is similar to making the final report for a project.

V.RESULT & DISCUSSION

The fundamental goal of our suggested study was to develop a well-fitting model,while eliminating underfit and overfit issues. We concluded that our model did not induceoverfitting or underfitting. When comparing training and test data, the model loss should be lower in training data. We discovered that deep learning systems, such as tensor flow and Keras, were advantageous when using neural nets to solve classification tasks.

The benefit was that if we understand these fundamental notions and how effective convolutional networks are, we can handle even the most challenging problems. Model loss in training examples should be smaller than in test data. We found that deep learning frameworks, such as tensor flow and Keras, were preferable when employing neural nets to perform classification tasks.

Convolutional networks could tackle the most challenging problems if we comprehended these core concepts and the learning curve. These powerful adjustment options could help us avoid fitting issues. The generalization difference wasthe steeper learning curve gap between the training and test loss.

Accuracy = Number of correctly predicted images Total number of images *100 Equation (5.1)

In this work, efficient automatic brain tumor detection is performed by using convolution neural network. Simulation is performed by using python language. The accuracy is calculated and compared with the all other state of arts methods. The training accuracy, validation accuracy and validation loss are calculated to find the efficiency of proposed brain tumor classification scheme. In the existing technique, the Support Vector Machine (SVM) based classification is performed for brain tumor detection. It needs feature extraction output. Based on feature value, the classification output is generated and accuracy is calculated. The computation time is high and accuracy is low in SVM based tumor and non-tumor detection.

Experimental dataset

We used the kaggle dataset for our experiment. We took a total of 2892 images with different types of tumours like T1, T2, and FLAIR. This dataset is consisting of two classes, where class 1 refers to tumour images and class 0 refers to non-tumour images. Some tumour datasets and non tumour dataset from our input images are shown respectively.

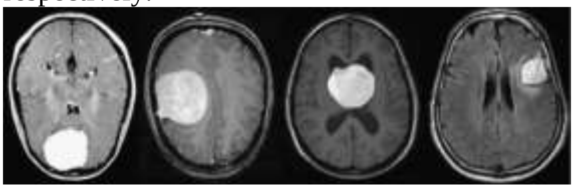

Figure 5.1 Image With Tumor

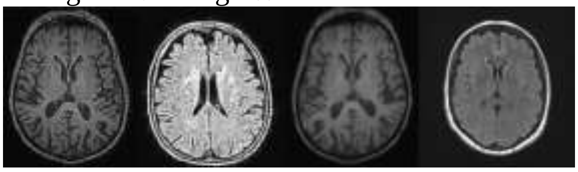

Fig. 6 Images Without Tumours.

Model Validation:

The model was trained for 24 epoches and these are the loss & accuracy plots

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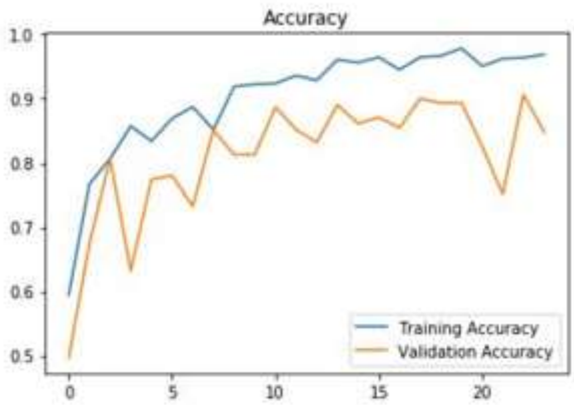

Figure 7 Comparing training/Validation Accuracy of CNN Model

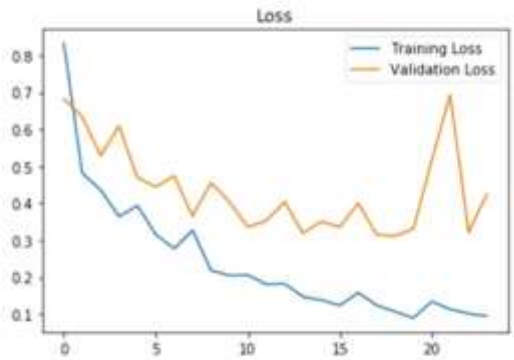

Figure 8 Comparing training/validation loss of CNN model

The best validation accuracy was achieved on the 23rd iteration.

The model is evaluated by applying the test image dataset. The confusion matrix for the predicted output is given as in the following Figure 5. The output of making prediction for the testing and validation given below.

testing: array([[81, 10], [12, 104]])

validation: array([[85, 9], [12, 80]])

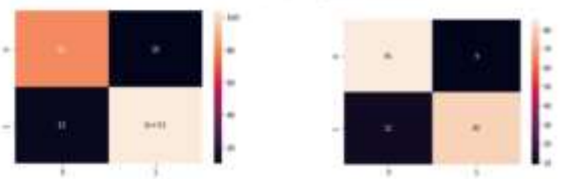

Figure 9 Confusion Matrix For The Testing & Validation Dataset Using CNN Model

output

The best validation accuracy was achieved on the 23rd iteration

Now, the best model (the one with the best validation accuracy) detects brain tumor with:

88.7% accuracy on the test set.

0.88 f1 score on the test set.
These resutls are very good considering that the data is balanced.
Performance table of the best model:

	Validation Set	Test Set
Accuracy	91%	89%
F1 score	0.91	0.88

Table : output of the Validation set and Test set

Figure 10 Final Output

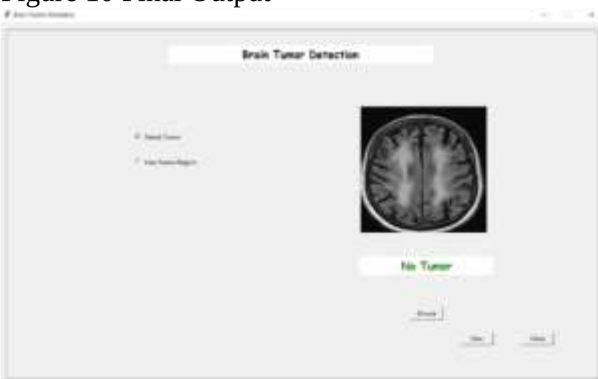

Figure 11 GUI Output

VI.CONCLUSION

The diagnosis of brain tumors is essential in clinical treatments. It is critical to interpret medical images because medical images vary greatly. The automatic brain tumor detection approach makes detection easier, but it also significantly increases the patient's chances of survival. Convolutional networks for brain tumor categorization have helped pave the way for better tumor detection and accuracy. MRI is most commonly used to detect and classify brain cancers. Due to the apparent efficient feature extraction capacity of DL-based techniques, they have recently gained greater attention and efficiency when compared to standard classification techniques for medical imaging. If cancer is diagnosed, many lives can be spared, and the appropriate grade is determined using quick and low-cost diagnostic tools. As a result, there is an urgent need to create rapid, non-invasive, and cost-effective diagnostic tools. This study made an attempt to meet such needs by bringing a novel solution for the detection of brain tumors in MRI images with greater precision. The proposed model integrated deep learning and transfer learning models to achieve a remarkable accuracy rate. As compared to similar techniques from past literature, in this study, the optimization of training models was increased to reduce the need for high computational power

Brain tumor detection system was developed using deep learning to detect tumors and find accuracy. Here, we have used an efficient method for automatic brain tumor classification using MRI images. The method is based on Transfer Learning and implemented on well-known CNN architectures. Transfer Learning has the benefit of decreasing the training time for a neural network model and can result in lower generalization error. The time-consuming process of brain tumor detection is thus simplified by automation. The comparative analysis of training accuracy versus validation accuracy is done. An accuracy of 89% on testing data and 91% on validation data is achieved by the proposed model for detecting brain tumor. In the context of the full dataset, it is necessary to parallelize and utilize high-performance computing platform for maximum efficiency. We tried our best to detect the tumors accurately but, nevertheless we faced some problems in our work where tumor could not be detected or falsely detected. So, we will try to work on those images and on the complete dataset. Hence, we will try to apply other deep learning methods in the future so that we can get a more precise and better result.

Limitations :

There are some limitations of our thesis work that we have listed in this section which we are leaving to improve in our future works.

• The Kaggle dataset has only 241 images

• Worked only on 2D images.

• Wecould have tried more traditional classifiers to increase the accuracy.

CNN is considered as one of the best technique in analyzing the image dataset. The CNN makes the prediction by reducing the size the image without losing the information needed for making predictions. ANN model generated here produces 65.21% of testing accuracy and this can be increased by providing more image data. The same can be done by applying the image augmentation techniques and the analyzing the performance of the ANN and CNN can be done. The model developed here is generated based on the trail and error method. In future optimization techniques can be applied so as to decide the number of layers and filters that can used in a model. As of now for the given dataset the CNN proves to be the better technique in predicting the presence of brain tumor.

FUTURE ENHANCEMENT

In future work, we can build a model of brain tumor for detecting several types of brain tumors and their region and how much percentage of the brain is affected through the cancerous cell. For ease of use, it can also be further deployed as an application.

There are more opportunities for improvement or research on our work in the future.

• Firstly, the number of images can be increased. The bigger the number of the images is, the better the model is trained.

• Secondly, we want to work on 3D images in future.

• Thirdly, more traditional classifiers can be applied to get more increased accuracy.

• Fourthly, we will try to classify the tumor if its benign or malignant after the detection of the tumor.

• Last but not the least, more variations of deep learning methods can be tested in future

Further, for better results, we implemented CNN which brought in the accuracy 97.87% with a split ratio of 80:20 of 217 images, i.e. 80% of training images and 20% of testing images. In the future, we plan to work with 3D brain images, achieve more efficient brain tumor segmentation. Working with a larger dataset will be more challenging in this aspect,and we want to build a dataset emphasizing the abstract with respect to our country which will accelerate the scope of our work.

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