Multi-class Brain Tumor Detection using Convolutional Neural Network

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***Abstract*—Brain tumour detection is one of the most critical and arduous function in the domain of healthcare. Brain tumour, if not detected at an early stage, can be fatal. At the present time, detection and classification of brain tumour is done by the method of Biopsy which is very time-consuming and complex. .By looking at the brain MRI or CT scan, it is possible for the experts to identify whether tumour is present or not and the region of the tumour, but it is difficult to identify the small dissimilarities in the structure of tumour and classify it into types. Hence this manual process gets stuck here for verification of type of tumour. For the sole purpose overcoming the above-mentioned gigantic hurdles we have pursued this research of multi-class brain tumour detection using deep learning. Our project will help doctors in quick decision-making regarding detection of the tumour and its type as well, and due to the early detection of the disease the treatment can be initiated at the right time, resulting in speedy recovery of the patient. We propose a deep learning model employing Convolutional Neural Network architecture which we have implemented using Keras and Tensorflow becauseit yields to a better performance than the traditional ones. In our research work, CNN gained an accuracy of 94.95%. Further, we have integrated our model with a web-app which we have built using Streamlit. Hence, users can provide their MRI scans via our web-app and get their medical results in a quick and efficient manner**.

Keywords—Brain tumour detection, MRI, Convolutional Neural Network, Biopsy, Keras, Tensorflow, Streamlit, Computer Vision:

I. INTRODUCTION

The brain is a torturous organ that regulates every action in our body's function, including thought, memory, emotion, touch, vision, temperature, and hunger. It is made up of more than 100 billion nerves which communicate in trillions of connections [2]. A brain tumor is a collection of dysfunctional cells in your brain that forms a lump. Your brain is protected by a highly tough skull. Any expansion in such a small location might generate complications. Early detection andclassification of brain tumors is a significant study subject in medical imaging, and it helps in the selection of treatment options. The most effective treatment technique for saving a person's life. Brain tumors can be classified in various ways such as Malignant and Benign, distinguished as cancerous andnon-cancerous respectively. A noncancerous brain tumor is an unexpected cluster of abnormal cells in your brain. Most grow slowly. They can't spread to other parts of your body the way cancerous tumors do. But they can grow large enough to causesymptoms and it is called a benign tumor. For instance, Meningioma and Pituitary, both are non-cancerous. Meningioma specifically, the tumor forms on the three layers of membranes that are called meninges. These tumors areoften slow-growing. As many as 90% are benign (not cancerous). A Pituitary tumor is a tumor that forms in the pituitary gland near the brain that can cause changes in hormone levels in the body. This illustration shows a smaller tumor (microadenoma). Pituitary tumors are abnormal growthsthat develop in your pituitary gland. There are many kinds of noncancerous tumors. Each affects a different type of brain cell, even though they aren't cancerous. In rare cases, these tumors can become cancerous. On the other hand, a cancerous brain tumor such as Glioma develops when cells grow uncontrollably. If the cells continue to grow and spread, the disease can become life-threatening. Malignant tumors cangrow quickly and spread to other parts of the body in a processcalled metastasis [13]. The cancer cells that move to other partsof the body are the same as the original ones, but they have theability to invade other organs. If lung cancer spreads to the liver, for example, the cancer cells in the liver are still lung cancer cells. In general, diagnosing a brain tumor usually begins with magnetic resonance imaging (MRI) [8]. Once MRI shows that there is a tumor in the brain, the most common way to determine the type of brain tumor is to look atthe results from a sample of tissue after a biopsy or surgery. The tumor can be identified quickly and accurately using digital image processing. Brain tumor segmentation was an important part of the study because it had complicated issues with accurate picture segmentation in brain disorders. To visually assess the patient, radiologists employ CT scans and MRIs. MRI images were used to analyze brain architecture, tumor size, and tumor location. In the conventional classification process, the classifiers often consider all the different segments of the image as equal and independentsegments. However, there are certain variations and 2 distinctions between these segments and few images possess weak inter-category features which can easily be classifiedand few images with strong attributes are difficult to classify. Latest technological advancements in deep learning (DL) havedemonstrated accelerated progress, and deep convolutional neural networks (CNNs) have super-seeded in brain tumor classification and segmentation. In particular, CNN hasachieved exemplary success in the field of image segmentation with its efficacy in employing a hierarchical classification structure. CNN is a brilliantly designed image segmentation technique wherein it enhances the feature representation attribute of the classifier by predicting entire low and high-level data and the feature extraction from the complex features are directly done from the data with increasing hierarchy. In the proposed research, and enhanced deep learning technique called Convolutional Neural Network (CNN) is presented. CNN is a feed-forward neural network mainly used for image recognition and processing. In thisresearch, CNN is trained for the automatic segmentation of brain tumors paper.

II. History & Background

The Historical and present solutions which are available, mostly use traditional machine learning algorithms, namely, K-Nearest Neighbours and Support Vector Machine. Artificial Neural Networks have been used in certain existing modelsbut they have yielded inaccurate results and low level of performance when put into production. Presence of multi-classdetection models is less, and those that exist mostly utilize Transfer Learning, using advanced and complex architectures and thus, require high-computing resources.

Our proposed model fills in these gaps by providing solutions to existing problems by facilitating brain-tumor detection, but not limited to detecting the presence of tumour, but furthermore, identifying the type of tumour among 3 types, namely, Meningioma, Glioma and Pituitary, with a high accuracyy .

III. LETERATURE SURVEY

Several methods have been proposed for brain tumor detectionand classification. Most of them focus on binary class classification such as benign and malignant. However, the binary class classification is easy due to the easy interpretation of tumor shape and texture. The multiclass classification problem is difficult due to the high similarity among tumor types.

Describes an approach for the order of MRI images Type equation here. , that depends on the back-propagation of neural system procedure. The strategy is built using the techniques of image enrichment, segmentation, registration, character recognition, and segregation. During the segmentation procedure, the morphological operations and threshold values are considered.This training image and experiment are analyzed by a neural network technique of a backpropagation algorithm to the recognition of the presence of a tumor [2].

Various algorithms developed to perform automatic brain tumor segmentation through MRI images and frequently used classifiers are not able to provide a straightforward solution to the image optimization techniques. A K-means clustering algorithm was proposed for performing brain tumor segmentation in MRI images [8].

Few of the methods involved in tumor detection overlap most of the time with the healthier tissue. Texture analysis is one of the useful techniques used to evaluate the structural orientation, regularity, harshness, and softness and distinguish between different regions of an image. Texture analysis provides convincing results as an image classifier to detect visible and non-visible scrapes with multiple applications in the MRI technique. Traditional classification methods employ grey-level pixel-based analytical attributes. Besides, different systematic and machine learning (ML) approaches were selected as image classifiers [8].

The method applied in this paper is based on Hough voting, a strategy that allows for fully automatic localization and segmentation of the anatomies of interest. It also used the learning techniques-based segmentation method which is robust, multi-region, flexible, and can be easily adapted to different modalities. Different amounts of training data and different data dimensionality (2D, 2.5D, and 3D) are applied in predicting the final results. Convolutional neural networks, Hough voting with CNN, Voxel-wise classification, and Efficient patch-wise evaluation through CNN are used in analyzing the image [12].

The capsule network is excellent for classification images compared to the CNN model. The pooling in capsule networks is not performed for down sampling, as further improvement intumor classification, can also be utilized for the fusion of deeplearning and handcrafted features [15].

From the literature survey; we can conclude that an ample amount of work is carried out in the classification of brain tumor images. But, only a few researchers have reported their work using CNN. Hence, the proposed work is taken.

IV. DESIGN ISSUES

Primarily, the decision to architect a Convolutional Neural Network instead of a normal Artificial Neural Network, plays a crucial role in providing the high accuracy as well as low storage cost due to the lesser number of training parameters. Determining the number of layers, their sequence and the various types of layers to be included while designing the architecture of the Convolutional Neural Network model is the most challenging design issue faced during our research. This design issue is overcome by referring the pre-existing models for similar problem statements and further performing hyper parameter tuning, hence tweaking the model to yield high accuracy for our problem statement.

Integration of the model with a web-app which makes it accessible to users with a user-friendly user-interface was a major design issue, which was the main differentiator of our research work. This design issue was resolved by using the Python's Streamlit framework which uses react to render the front-end on the web browsers.

V. METHODOLOGY

Since the main objective of the research work is to build a Convolutional Neural Network model, capable of classifying MRI brain scan images into four categories of brain tumour, namely, No Tumour, Malignant, Glioma, Pituitary and further making the model accessible to the users via a web-app, the methodology employed, consists of various stages from Data Collection to Model Deployment.

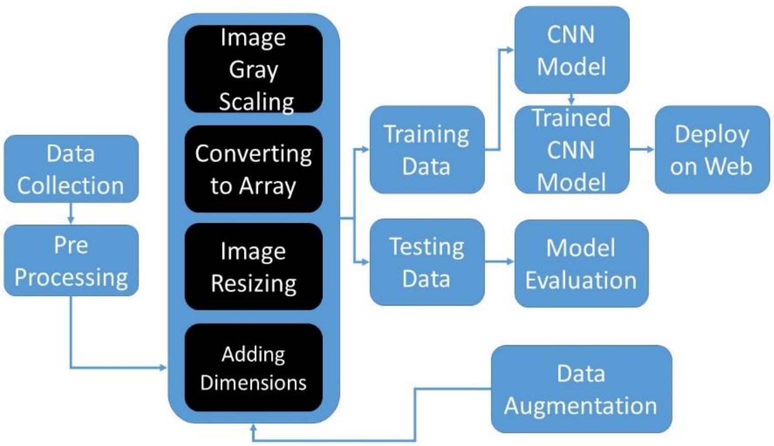

Fig. 1. Proposed System

A. Data Collection:

We have chosen to work with the dataset from Kaggle, an open-source dataset repository, which consists of total 3264 images which are MRI scans of brain of real people. The images are examined by radiologists and approved to be authentic.

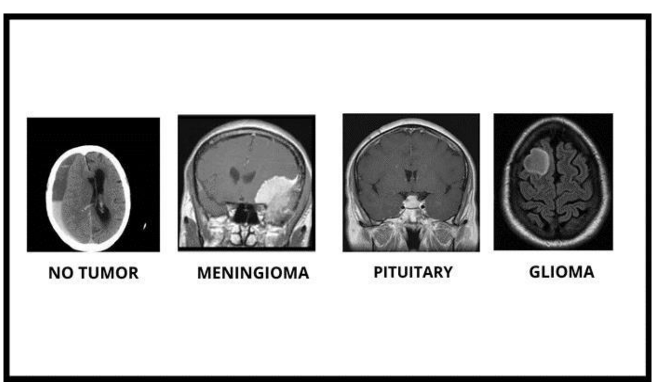

Fig. 2. An instance of MRI scan images present in our dataset

B. Image Data Preprocessing:

1) *Image resizing:* Resizing images is a critical preprocessing step in computer vision .An input image that is twice as large requires our network to learn from four times as many pixels and that time adds up. Moreover, many deep learning model architectures require that our images are the same size and our raw collected images may vary in size.

2) *Image greyscalilng:* Images that have been processed into grayscale, then the head position is determined for each image. Each image has a variety of sizes and positions so that the head size and position are uninformed by removing the black sides on the left, right, front, and back of the head. After that, the resolution is resized to 150 x 150 pixels. It is performed by using some computation.

3) *Converting into array:* Converting an image to an arrayis an important task to train a machine learning model basedon the features of an image.

Adding dimensions: Dimensionality holds for the inhomogeneity of image dimensions since it separates the scaling of the image into a scaling along the *x-y* plane and a scaling along the gray tone axis. This allows us to review the fundamental measurements on sets to determine those satisfying the dimensionality criterion. Then, we show that dimensionality is of equal importance when processing images.

C. Defining the Model's Architecture:

A sequential model comprising of multiple complex and diverse layers has been defined using Keras. The architecture of the CNN model is different for different problem statementsand datasets; an architecture yielding high accuracy for one problem may not do the same when applied to other problem statements.

The model proposed in our research has an architecture that comprises of Convolution Layers which convolve the input image by the virtue of a 3X3 dimensioned kernel, followed by Pooling Layers which perform feature extraction by using the Max Pooling technique, which extracts the features based on high magnitude values of pixels in the input image. In order toprevent overfitting of the model, Dropout Layers have been utilized, as the name suggests, the layer drops out a neuron and trains the model for the particular iteration, in case of our model, each neuron has been assigned the probability of 0.25 of dropping out.

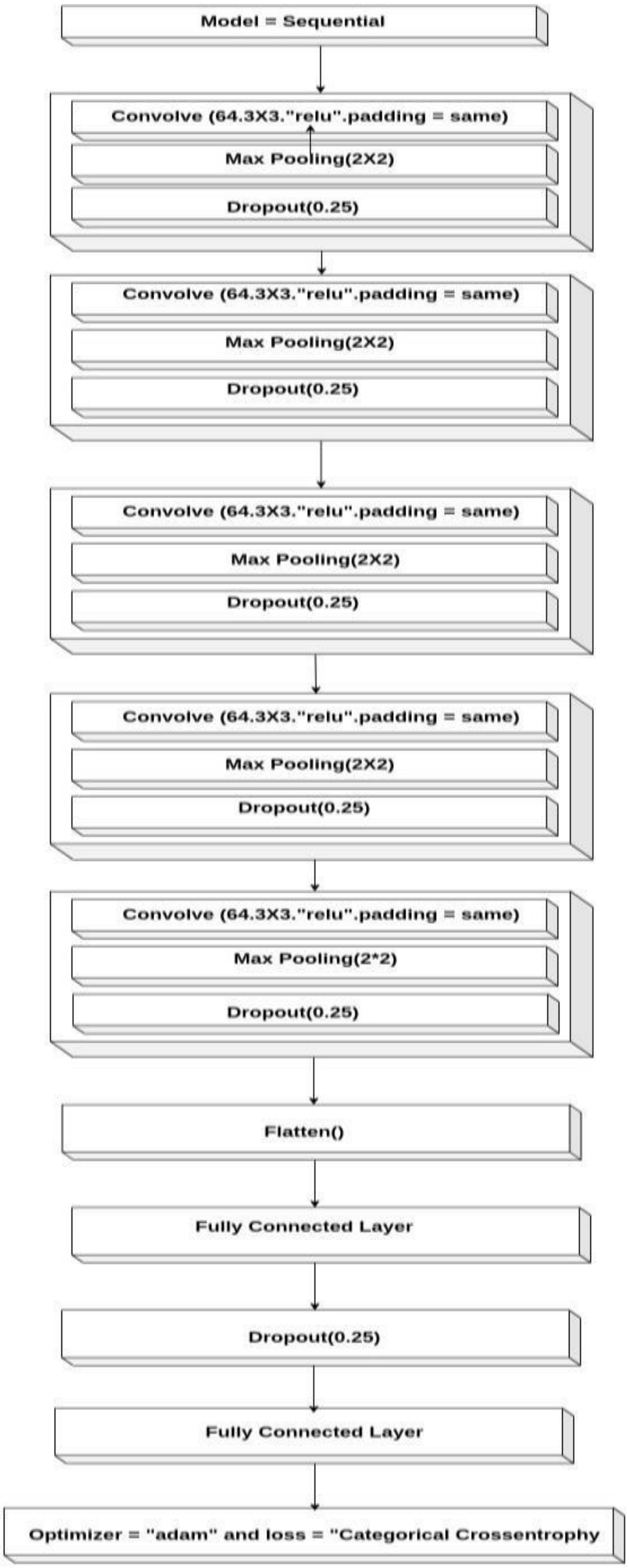

Fig. 3. Architecture of the CNN model

The architecture of our CNN model comprises of various types of layers, and each type of layer serves a different purpose. Following are the types of layers employed in our CNN architecture:

1) Convolutional Layer: Resizing images is a critical preprocessing step in computer vision .An input image that is twice as large requires our network to learn from four times as many pixels and that time adds up. Moreover, many deep learning model architectures require that our images are the same size and our raw collected images may vary in size. ReLU has been utilized as activation function. The rectified linear activation function or ReLU for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance. Formula: max (0, z).

2) Max-Pooling Layer: Resizing images is a critical preprocessing step in computer vision .An input image that is twice as large involves down sampling of features. It is applied through every layer in the 3d volume. Typically there area hyper parameters within this layer: The dimension of spatial extent: which is the value of n which we can take N cross and feature representation and map to a single value.Stride: which is how many features the sliding window skips along the width and height A common pooling layer uses a 2 cross 2 max filter with a stride of 2, this is a non-overlapping filter. A max filter would return the max value in the features within the region. Example of max pooling would be when there is 26 across 26 across 32 volume, now by using a max pool layer that has 2 cross 2 filters and astride of 2, the volume would then be reduced to 13 crosses, 13 crosses 32 feature map.

3) Dropout Layer: The Dropout layer is a mask that nullifies the contribution of some neurons towards the next layer and leaves unmodified all others. We can apply a Dropout layer to the input vector, in which case it nullifies some of its features; but we can also apply it to a hidden layer,in which case it nullifies some hidden neurons. Dropout layersare important in training CNNs because they prevent overfitting on the training data. If they aren't present, the first batch of training samples influences the learning in a disproportionately high manner. This, in turn, would prevent the learning of features that appear only in later samples or batches.

4) Fully Connected Layer: Lastly, is the Fully Connected Layer**,** which involves Flattening. This involves transforming the entire pooled feature map matrix into a single column which is then fed to the neural network for processing. With the fully connected layers, we combined these features together to create a model. Finally, we have an activation function such as softmax or sigmoid to classify the output. In our model, since we are dealing with multi-class classification, we have employed the Softmax function:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

σ = softmax

$\vec{z}$ = input vector

e^{z_i} = standard exponential function for input vector

K = number of classes in the multi-class classifier

e^{z_j} = standard exponential function for output vector

e^{z_j} = standard exponential function for output vector

(1) Mathematical equation of Softmax function

D. Model Compilation:

After the architecture has been defined, the model must be compiled before it is availed for the process of training. This step involves finalizing the loss function, optimizer as well as the metrics to be used while evaluating the performance of the model. We have initialized the learning rate of the model as 0.001, which is further tweaked leading to an optimal performance of the model, by the adam optimizer. Adaptive Moment Estimation is an algorithm for optimization technique for gradient descent. The method is really efficient when working with large problem involving a lot of data or parameters. It requires less memory and is efficient. Intuitively, it is a combination of the 'gradient descent with momentum' algorithm and the 'RMSP' algorithm.

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] v_t = \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2$$

Parameters Used:

1. ϵ = a small +ve constant to avoid 'division b0' error when (v_t -> 0). (10^{-8})
2. β_1 & β_2 = decay rates of average of gradients in the abovetwo methods. ($\beta_1 = 0.9$ & $\beta_2 = 0.999$)
3. α — Step size parameter / learning rate (0.001)

(2) Mathematical equation of the adam optimizer

Categorical cross-entropy has been used as the loss function. This is the most suitable loss function for our model, sincewe have a one-hot encoded dataset also since our model does multi-class detection.

E. Model Training and Testing: Data augmentation has been performed prior to feeding the data to the CNN model for training it. To be precise, thehorizontal flipping of MRI brain scan training images is done to feed a variety of data considering real-world use-cases ofthe model, hence leading to a generalized model. The data is bifurcated into two parts 80% training and 20% testing. We have trained the CNN model using training data at a learning rate of 0.001. Epoch: indicates the number of passes of the entire training dataset the machine learning algorithm has completed. We have trained the model in 50 epochs and obtained training accuracy of 98.48%. The performance of model has been tested using the testing data with the accuracy of 94.95%.

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The architecture of a CNN is analogous to that of the connectivity pattern of neurons in the human brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field, known as the Receptive Field. A collection of such fields overlap to cover the entire visual area. The early layers of a neural network detect edges from the input image. Deeper layers might be able to detect the cause ofthe objects and even more deeper layers might be able to detect the cause of the complete object. CNN consists of two parts: feature extraction and classification. CNN architecture generally includes five main layers: input layer, convolution layer, pooling layer, fully connected layer and classification layer. CNN performs feature extraction and classification through sequentially trainable layers placed one after the other. Feature extraction part of the CNN generally includes the convolutional and pooling layers, whereas the classification part includes the fully connected and classification layers. Because the our CNN model is designed to classify a given image into 4 classes, the output layer has five neurons. The last fully connected layer, which is a four-dimensional feature vector, is given as an input to softmax classifier, which makes the final prediction about the tumor type.

F. Model Evaluation:

We have evaluated the performance of model by using the model evaluation metric defined during the model compilationphase, which is accuracy.Accuracy refers to the fraction of predictions that the Convolutional Neural Network model got right. Since, ourmodel is for multi-class classification, the accuracy metric is mathematically defined as follows:

Accuracy = (Correct Predictions) ÷ (Total Number of Example)

(3) Mathematical equation for multi-class accuracy metric since, we have a balanced image dataset, accuracy

is a provensuitable metric for model evaluation.

G. Model Deployment: Prior to deploying the model on the web, it is saved in the h5 format and loaded for deployment. Deploying the model on the web allows the users (potential patients) to be able to utilize it for detecting brain tumour and its type as well. Also, this gives us an idea regarding how our model performs in the real-world. An open-source framework of Python, called as Streamlit has been used to build the web-app. Finally, ngrok has been used to put our local development server on theinternet. The web-app is hosted on one of the domains that are the sub-parts of ngrok and hence there is no need of a public domain or IP. The web-app is accessible via both, a personal computer and even a smartphone with an internet connection. The user can upload his/her MRI brain scan image of size upto 200KB (Kilo-bytes) from local storage via browsing or even via drag-and-drop method onto the web-app's user-interface. The backend of the web-app has the saved CNN model integrated in it, thus, the input image sent by user via frontend is fed to the model for classification, as soon as the pre-processing is finished. Finally, the classification output of themodel is shown as a result to the user via the user-interface.

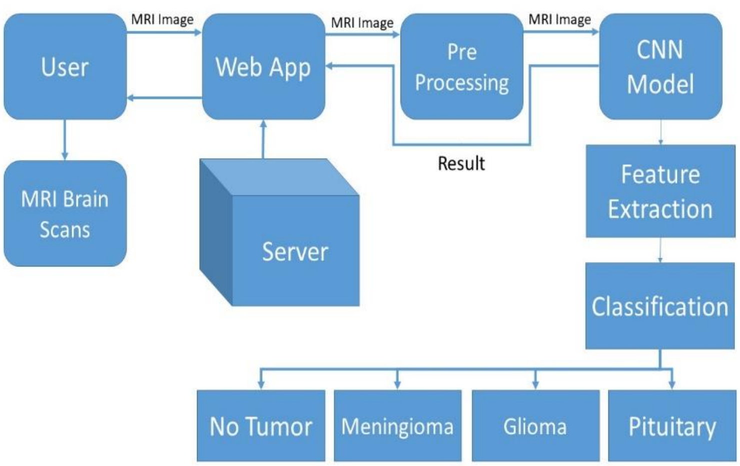

Fig. 4. Working of the classification system post-deployment

VI. Result And Analysis

The model has been trained on multiple epochs, to be precise, 50 epochs i.e. the performance of the model has beenmonitored for total 50 passes of the entire dataset to the model. The metric for evaluation is accuracy. Apart from accuracy, the loss evaluated by the categorical cross-entropyloss function has been monitored over all the epochs as well phase which is, accuracy.

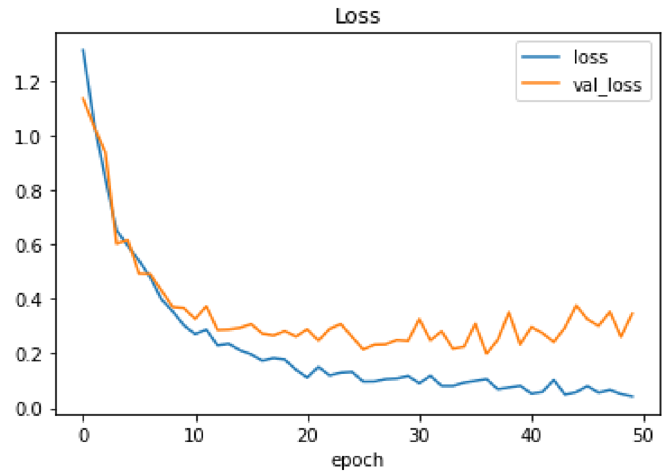

Fig. 5. Loss per epoch graph

The above graph depicts the declination of the validation loss as well as loss which occur per epoch. As we see, the loss decreases after each epoch and is marginally decreased at the end, as compared to the loss that occurred at the beginning. Apart from loss, the graph for accuracy also has been plotted per epoch. We started with a training loss of 1.3148 and validation loss of 1.1355, and at the end of 50th epoch we got training loss of 0.0425 and validation loss of 0.3460. Thus, the loss has been minimized to a great extent.

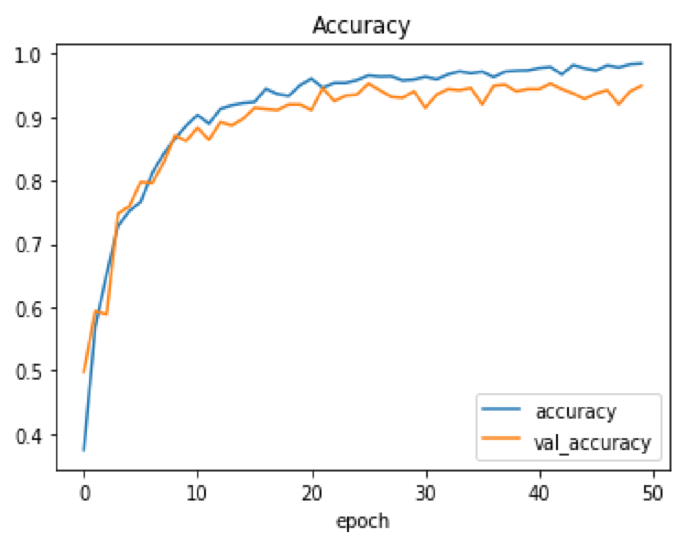

Fig. 6. Accuracy per epoch graph

The graph in Fig. 6. Depicts the increment of the validation accuracy as well as training accuracy which occur per epoch. As we see, the loss decreases after each epoch and is marginally increased at the last epoch, as compared to the accuracy that occurred at the beginning. At the 1st epoch, the training accuracy was 37.50% and the validation accuracy was 49.83%, eventually after the 50th epoch, the training accuracy increased to 0.9848 and the validation accuracy increased to 0.9495.

VII. CONCLUSION

Enabling cost-effective and reliable detection of brain tumour and its type has been facilitated by our research work which proposes a Convolutional Neural Network model having atraining accuracy of 98.48% and a testing accuracy of 94.95%. Furthermore, the model has been integrated into a web-app with a user-friendly user-interface, thus, allowing users to obtain results from their MRI brain scan images. The proposedresearch work solves a real-world challenge faced by the health-care industry. In the near future, the research work can make further progress by optimizing the process of architecting the model, and employing the higher computing resources as well as utilizing transfer learning by using pre-trained architectures such as VGG-16 and Inception-V3 for better feature extraction. The custom CNN model can then be built on top of these state-of-the-art models.

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REFERENCES

[1] Tonmoy Hossain, Fairuz Shadmani Shishir, Mohsena Ashraf MD Abdullah Al Nasim, Faisal Muhammad Shah,” Brain Tumor Detection Using Convolutional Neural Network”

[2] Sunil Kumar, Renu Dhir, Nisha Chaurasia” Brain Tumor Detection Analysis Using CNN”

[3] S. Gobhinath; S. Anandkumar; R. Dhayalan; P. Ezhilbharathi; R. Haridharan “Human Brain Tumor Detection and Classification by Medical Image Processing”

[4] Shanaka Ramesh Gunasekara, Maheshi B. Dissanayake “A SystematicApproach for MRI Brain Tumor Localization and Segmentation Using Deep Learning and Active Contouring.”

[5] Praveen Gamage “Identification of Brain Tumor using Image ProcessingTechniques”

[6] Darshan Bhamare darshanbhamare, Vijay Sawale, Maharashtra VinayGupta, Ajay Ghosade “Brain tumor detection and classification using convolutional neural network”

[7] Prof. Asha. P., Ashwini Patne, Laxmibai, Pooja.D.H, Jyoti Patil “BrainTumor Detection using Convolutional Neural Network”

[8] Roohi Sille, Tanupriya Choudhury *, Piyush Chauhan, Durgansh Sharma “Dense Hierarchical CNN – A Unified Approach for Brain Tumor Segmentation”

[9] Neha Sharma, Mradul Kumar Jain, Nirvikar and Amit Agarwal “BRAINTUMOR CLASSIFICATION USING CNN”

[10] Hapsari Peni Agustin Tjahyaningtijas, Dewinda Julianensi Rumala Cucun Very Angkoso Nurul Zainal Fanani Joan Santoso Anggraini Dwi Sensusiati Peter M.A van Ooijen Ketut Eddy Purnama, Mauridhi HeryPurnomo “Brain Tumor Classification in MRI Images Using En-CNN”

[11] Jayashree Shedbalkar, Haliyal Dr. K. Prabhushetty “ConvolutionalNeural Network based Classification of Brain Tumors images”

[12] P Gokila Brindha “Brain tumor detection from MRI images using deeplearning techniques”

[13] Emrah Irmak “Multi-Classification of Brain Tumor MRI Images UsingDeep Convolutional Neural Network with Fully Optimized Framework”

[14] Kasiful Aprianto “Brain Tumors Detection By Using ConvolutionalNeural Networks and Selection ofThresholds By Histogram Selection

[15] Isselmou abd El Kader, Guizhi Xu , Zhang Shuai ,Sani Saminu, ImranJavaid, Isah Salim Ahmad, Souha Kamhi “ Brain tumor Detection and Classification on MRI Images by a Deep Wavelet Auto-Encoder Model”