International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 07 | July 2022 www.irjet.net p-ISSN: 2395-0072

AI Based Approach for Classification of MultiGrade Tumour in Human Brain

Dheeraj D[1], Pooja Tapas[2], and Rithika R[3],Nithish P[4],Rashmi M[5]

[1]*Assistant Professor, Global Academy of Technology*
[2,3,4,5]*Undergraduate Student, Global Academy of Technology*

---***---

***Abstract**-An essential step in the processing of medical image data is the classification of images of brain tumours. The idea of biomedical imaging is significant because doctors may utilize it to create precise diagnoses and treatment plans. Magnetic resonance imaging (MRI) is one of the most widely used imaging methods for examining brain tissue (MR imaging). A tumour forms when malfunctioning cells group together and solidify into a mass of tissue. Tumors can develop in bones, skin, tissue, organs, and glands. Benign and malignant tumours can be further divided into meningioma, glioma, and pituitary tumours. The purpose of this study is to present an AI-based method for categorising multigrade tumours in the human brain. As we move forward with this study, we'll be using the four models U-net, VGG-16, AlexNet, and ResNet50 for datasets that are small and medium-sized. We found that AlexNet's accuracy for normal classification was 99 percent, and that for multigrade classification, we attained an average IOU of 77.5 percent*.

Keywords- Unet, AlexNet, ResNet, Vgg16, Meningioma, Glioma, Pituitary tumor

1. INTRODUCTION

Biomedical imaging is a group of techniques that can be used to look inside a body's internal organs without performing surgery on it. Image segmentation is used in medical imaging processing to identify tumours and provide helpful information for additional diagnosis.

The objectives of picture segmentation in medical imaging processing include tumour identification and effective findings for further diagnosis. A brain tumour is an abnormal growth of brain cells that may be cancerous, non-cancerous, or both types of cells. The two most prevalent types of cancer are benign and malignant. A brain tumour that is malignant begins in the brain and swiftly spreads to the tissues around it. On the other hand, benign tumours develop gradually. Depending on the type, size, and location of the brain tumour, there are different treatment options available. Therefore, it is crucial to classify brain tumours in order to determine which form of brain tumour a patient actually has. Planning the course of treatment is therefore a crucial step in enhancing patients' quality of life. As a result, we suggest a system for classifying multigrade cancers. In this work, we present a useful system for classifying and identifying brain tumours.

2.LITERATURE SUMMARY

Sl. No	Author	Year of Publication	Methodology	Results obtained
1	Nudrat Nida, et Al [3]	2021	CNN architecture	Deep features combined with ELM classifiers produce accurate melanoma recognition models.
2	EmrahImarak,et Al [4]	2021	Convolutional neural network	Hyperparameter optimization in CNN
3	Tobias Hinz, et Al [5]	2018	Deep CNN	The hyperparameters can be optimised on a series of smaller representations that grow in size until the original data size is reached.
4	Jiawei Lai, et Al [6]	2019	U-net, CNN	The IBSR 18 dataset's experimental brain MRI results demonstrated the efficiency of GMMD-U on segmentation tasks.
5	Asma Naseer, et Al [7]	2021	Deep Learning	The average accuracy is roughly 98.8%.
6	Awwal Muhammad Dawud, et Al [8]	2019	CNN, AlexNet, and AlexNet-SVM	"CNN, AlexNet, and AlexNet-SVM attained accuracies of 90.65%, 92.13 percent, and 93.48 percent, respectively."[8]
7	QIANG LI, et Al [9]	2021	AlexNet,GoogleNet, VggNet,DenseNetResNet,SqueezeNet, ShuffleNet,MobileNet,	A brain tumour is a neurological condition that can manifest as a malignant or non-cancerous mass, or as the growth of a tumour. AlexNet, Vggnet, and DenseNet all have results above 0.95. ResNet.On a noise-free image, it's a 0.7663.
8	MortezaEsmaeili, et Al [10]	2021	GoogLeNet, MobileNet,DenseNet-121	On the testing dataset, the considered models had the precision of 92.1%, 87.3%, and 88.9%.
9	Kai Klinker, et Al [11]	2019	Augmented Reality	Improved Diagnosis Precision
10	Muhammad Sajjad, et Al [12]	2018	InputCascadeCnn,VGG-19	For grades 1,2,3, and 4, the accuracy utilising the radiopaedia dataset is 90.03 percent, 89.91 percent, 84.11 percent, and 85.50 percent, respectively.

3.METHODOLOGY

3.1. Proposed Methodology

The suggested model aims to increase the precision and accuracy of the outcomes. We are working to improve the accuracy of the system in an effort to lower the high death rate caused by cancers. Our project's initial phase is the acquisition of the dataset, which consists of MRI pictures, followed by data cleaning and transformation, which is mostly done to convert the collected dataset into the necessary format. To remove noise and undesirable data components, the next step is to preprocess the data. In this step, the image is enhanced and the undesired text and noise are removed. Additionally, the data is segmented to separate the tumor, cerebrospinal fluid, white matter, and gray matter. After the preprocessing stage, the clean data is obtained. After that, we start the classification training, which involves teaching the system how to categorize a multigrade brain tumor. The classification algorithms offered by the CNN architecture are used in this step. The system must then be tested to ensure that the results are exact and accurate when the training process is complete.

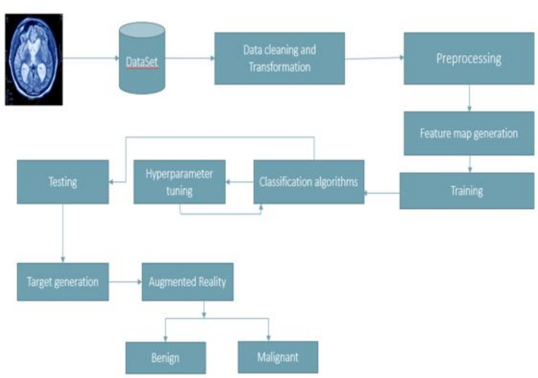

Fig. 3.1.1. Proposed Methodology

3.2. Dataset

3.2.1. Data collection

In this study, we propose a classification model that would allow us to use the patient's MRI pictures as an input and compute whether a brain tumor is present or not as an output. We used Kaggle, which makes MRI scans of the brain available to the public.

3.2.2. Data augmentation

Data augmentation is a method for intentionally increasing the volume and complexity of already-existing data. To increase the size of training sets and give developers access to more representative training data, data augmentation techniques have been used. The fundamental idea is to artificially boost the quantity of training instances. It can function as a regularizer to stop neural networks from overfitting. However, although the study says data augmentation is not fully recommended for medical imaging experimentation, in our work due to acute shortage of data the experiments have been carried out using synthetic data keeping in mind the positional invariant features capture which would significantly enhance models' performance.

3.3. Preprocessing

Image pre-processing techniques aim to enhance images for the sake of further processing (generally object recognition). Pre-primary processing's objectives are noise reduction (the source of noise is typically digitizing and transmission), the elimination of distortion caused by the scanning device, and finally, the suppression or highlighting of other attributes that are crucial for subsequent processing, segmentation, and edge detection.

3.4. Classification

The suggested approach includes identification of the region for analysis, drawing out the feature maps,electing the right prominent feature value, and diagnosing them into the right class. All the features that are retrieved make up the feature subset which includes most of the distinguished features supplied for classification and the experiment was progressive until a drop in the performance was seen. In order to compare these three pattern classification techniques: U-net, AlexNet and Vgg16.

3.5. Performance Measures

The methods were applied to a class of MRI images, historically identified as Benign or Malignant and classified using U-net, AlexNet, and Vgg16 architectures to record the contrast between their performances. The accuracy of Vgg16 model was found to be 66% for medium dataset and 90% for small dataset, for U-net model it was 74% for medium dataset and 92% for small dataset and AlexNet showed an accuracy of 99% model for both small and medium datasets.

4. Results and Discussion

The following Neural Network architectures have been experimented and their performance has been recorded:

4.1. U-net:

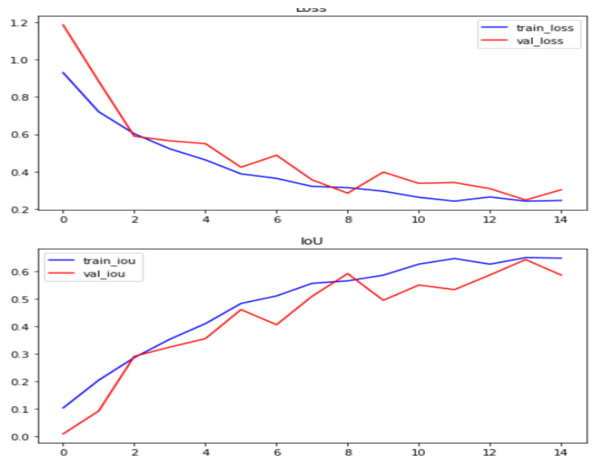

Fig.4.1.1 Accuracy graph for medium dataset

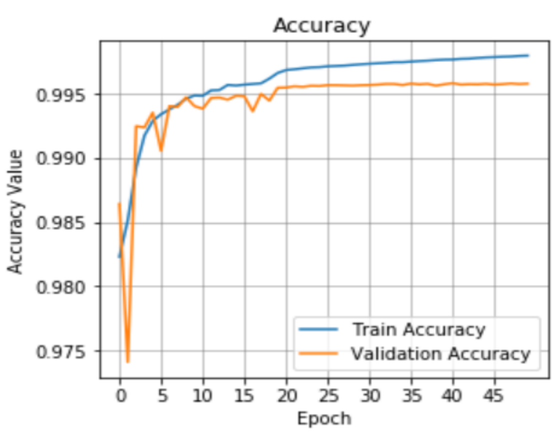

Fig.4.1.2 Accuracy graph for small dataset

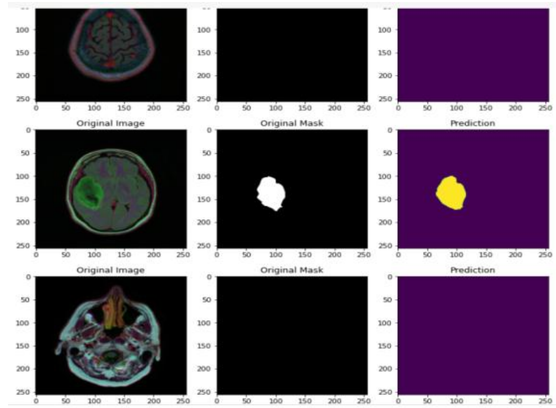

Fig. 4.1.3 Prediction for medium dataset

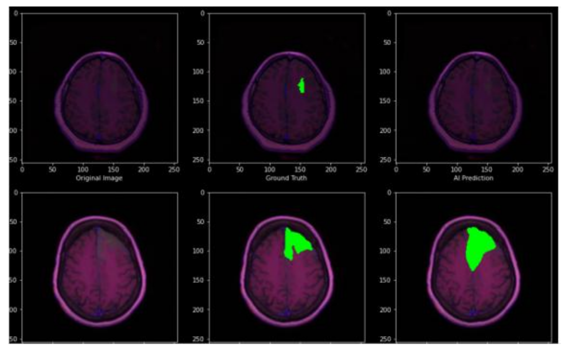

Fig. 4.1.4 Prediction for small dataset

4.1.1. Experimentation Dataset

The small dataset consisted of 250 images with 155 that showed the presence of tumor and 98 that did not show any tumor. For the medium dataset we considered around 4000 images with 2556 images that had tumors and 1373 that did not show any tumor.

4.1.2.Data Augmentation

On a dataset of roughly 4000 MRI images for brain tumour detection, the proposed approach was examined and tested.

In order to improve the performance of the network, data augmentation aims to increase the original training data's volume. There have been many different data augmentation methods applied. Simple transformations like flipping, rotating, shifting, and zooming can cause displacement fields to images but do not result in training samples with significantly altered shapes. Because tumours lack a defined structure, shear surgery can only slightly affect the tumor's general form in the horizontal direction, which is not enough to offer enough varied training data

4.1.3.Training and Optimization

To minimize the cost function with regard to its parameters, stochastic gradient-based optimization is needed when training deep neural networks. Adam typically updates and corrects the moving average of the current gradients using the first and second moments of the gradients. The Soft Dice metric, as opposed to the cross-entropy based or the quadratic cost function, was employed as the network's cost function throughout the training process.

4.2 Vgg16:

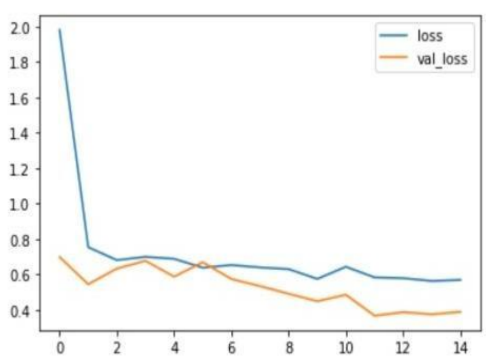

Fig.4.2.1 Accuracy graph for medium dataset

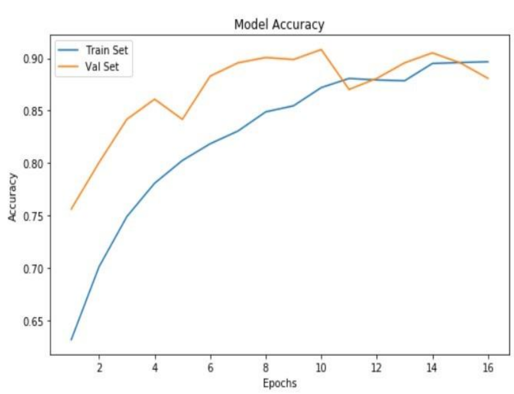

Fig.4.1.2 Accuracy graph for small dataset

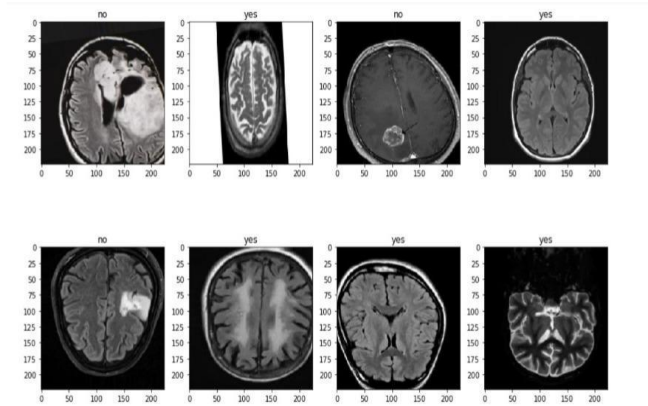

Fig. 4.2.3 Prediction for medium dataset

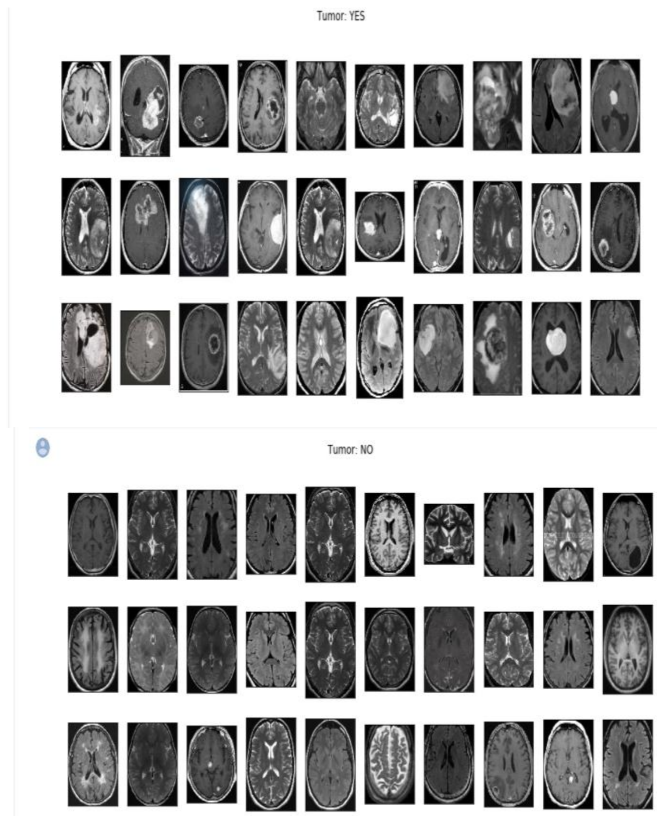

Fig. 4.2.4 Prediction for small dataset

4.2.1. Dataset

The small dataset consisted of 2000 images with 1085 that showed the presence of tumor and 980 that did not show any tumor. For the medium dataset we considered around 6000 images with 3255 images that had tumors and 2940 that did not show any tumor.

4.2.2.Pre-processing

Using the VGG-16 model, we studied how to correctly evaluate performance while detecting brain tumours. The first step will be to resize the data set's images to (224x224) and pre-process them in order to prepare them as inputs for the VGG-16 model. Every image in the data set has undergone pre-processing. Here we are using pre-processing techniques like normalization ,resize, label and shuffle .The first step in pre-processing is normalization where the Brain image is cropped from the MRI. The second step of pre-processing is to identify the highest contour so that here the edges of the brain are found and this image is taken as a pre-processed image.

4.2.3. Training

The images were enhanced and produced for pre-processing before they were sent to training. The training set is utilized to develop and fit the model, the validation set offers an overall analysis of the trained model and finally the model's hyper-parameters such as epoch, learning rate are considered for improving the performance of the classifier. Here we have used adapting learning rate with epoch 40,60,80,90. The test set offers an accurate review of the finished model.

4.2.4. VGG16

A pretrained VGG-16 model with all the parametric weights needed for the imagenet classifier set has been feeded considering one particular parameter to add the weights. Since the experiment here is carried out to classify into two classes only, the custom classifier is being devised with the two classes accordingly. Edges, lines, and blobs are low level picture elements that are extracted, and the fully connected layer then divides them into two groups. After the creation of the model ,the accuracy is checked and we test whether the model predicts the tumour or not.

4.3. AlexNet

```
train loss: 100%[**************************************************->]0.001
[epoch 27] test_loss: 0.028  test_accuracy: 0.988
train loss: 100%[**************************************************->]0.000
[epoch 28] test_loss: 0.063  test_accuracy: 0.988
train loss: 100%[**************************************************->]0.000
[epoch 29] test_loss: 0.052  test_accuracy: 0.964
train loss: 100%[**************************************************->]0.000
[epoch 30] test_loss: 0.088  test_accuracy: 0.972
Finished Training
```

Fig.4.3.1 Accuracy for epoch 60

```
train loss: 100%[**************************************->]0.000
[epoch 27] test_loss: 0.050  test_accuracy: 0.937
train loss: 100%[**************************************->]0.000
[epoch 28] test_loss: 0.059  test_accuracy: 0.957
train loss: 100%[**************************************->]0.000
[epoch 29] test_loss: 0.060  test_accuracy: 0.976
train loss: 100%[**************************************->]0.000
[epoch 30] test_loss: 0.024  test_accuracy: 0.996
Finished Training
```

Fig.4.3.2 Accuracy for epoch 40

```
[epoch 26] test_loss: 0.044  test_accuracy: 0.988
train loss: 100%[************************************************************->]0.000
[epoch 27] test_loss: 0.039  test_accuracy: 0.988
train loss: 100%[************************************************************->]0.000
[epoch 28] test_loss: 0.051  test_accuracy: 0.980
train loss: 100%[************************************************************->]0.000
[epoch 29] test_loss: 0.042  test_accuracy: 0.980
train loss: 100%[************************************************************->]0.002
[epoch 30] test_loss: 0.049  test_accuracy: 0.988
Finished Training
```

Fig.4.3.3 Accuracy for epoch 50

4.3.1. Data Augmentation

On a dataset of roughly 6000 MRI images for brain tumor detection, the proposed approach was examined and tested.The goal of data augmentation is to increase the amount of synthetic data which is essentially needed in order to track and increase the performance of model.AlexNet employs two methods for data augmentation. The first feeds random input image cropping, rotations, and flips into the network as it is being trained.Due to the presence of fully connected layers, input size is fixed.

4.3.2. Preprocessing and Training

To obtain steps with a high degree of precision, preprocessing is necessary. Patient-specific artefacts include ring, staircase, and volume effect artefacts, as well as MRI and CT scans. All of these are eliminated before analysis utilising some preprocessing techniques. The suggested approach shows how a set of MRI images can be categorised using transfer learning to retrain the AlexNet convolutional neural network. Following the creation of the network structure, training options are discussed. Stochastic momentum gradient descent optimization model, histogram equalisation, starting learning rate, and epochs—which denotes the entire training period on the training dataset—are some of the training options. By training the datasets with different epochs, such as 40, 50, and 60, hyper parameter tuning is accomplished. The network was trained using preset training datasets, layer designs, and training choices. The classification module receives the test image and uses a trained network to forecast or classify the supplied image into various categories.

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 07 | July 2022 www.irjet.net p-ISSN: 2395-0072

The following Neural Network architectures have been experimented for classification of multigrade and their performance has been recorded:

4.4.U-Net:

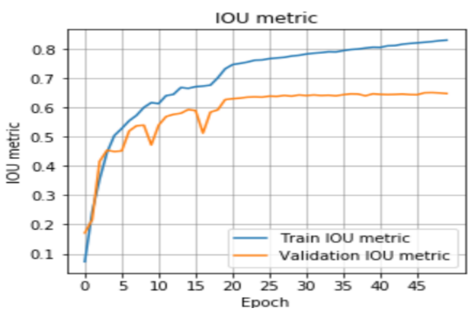

Fig.4.4.1. Accuracy graph

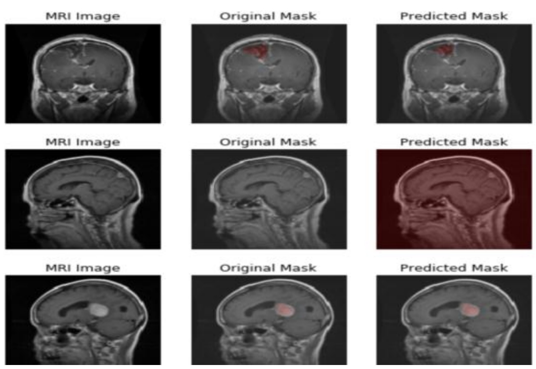

Fig.4.4.2. Predicted Graph

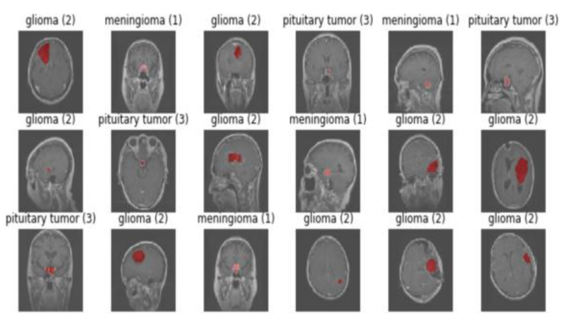

Fig.4.4.3. Predicted Output

4.4.1. Dataset

The dataset consisted of 708 meningioma positive images, 1426 glioma tumor images and 930 pituitary tumor images.

4.4.2.Training

The input photos and their associated segmentation maps are used to train the network using Caffe's version of stochastic gradient descent. The unpadded convolutions cause the output image to be a constant border width smaller than the input image. We reduce the batch to a single image to reduce overhead and make the most of the GPU RAM by prioritising large input tiles over a large batch size. We pre-compute the weight map for each ground truth segmentation to take into account the fluctuating frequency of pixels from a certain class in the training data set and to force the network to learn the small separation barriers that we impose between touching cells. A good initialization of the weights is crucial in deep networks with numerous convolutional layers and varied network routes. Otherwise, some sections of the network could activate too much while other parts never do.

4.4.3.Data Augmentation

Since there is a shortage of training samples for any model to adapt and learn, data augmentation was sought to teach the neural network to handle invariance and flexibility of features. On a rough 3 by 3 grid, we produce smooth deformations using random displacement vectors.

4.4.4.Experiment

We use three separate segmentation tasks to show the u-net in action. The segmentation of neural structures in recordings made using an electron microscope is the first challenge. We employed a brain-tumor segment dataset for this experiment, which is accessible online. 3064 MRI scans and 3064 masks are included. A collection of 30 images serially sized 512x512 section which transmits through electron microscopy of the ventral nerve cord of a Drosophila serves as the training data (VNC). To proceed with the implementation and classification, the ground truth data which is completely tagged for each image is considered for the white and back matter of the images. U-net model has been chosen for the experimentation as this model does not need any further processing either before or after diagnosis which internally makes the model less prone for the errors and as well ensure that it outperforms other classifiers which may need to be trained with strong feature maps after careful processing of the data. However the U-net model also suffers a warp and random error.

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 07 | July 2022 www.irjet.net p-ISSN: 2395-0072

4.5. ResNet50

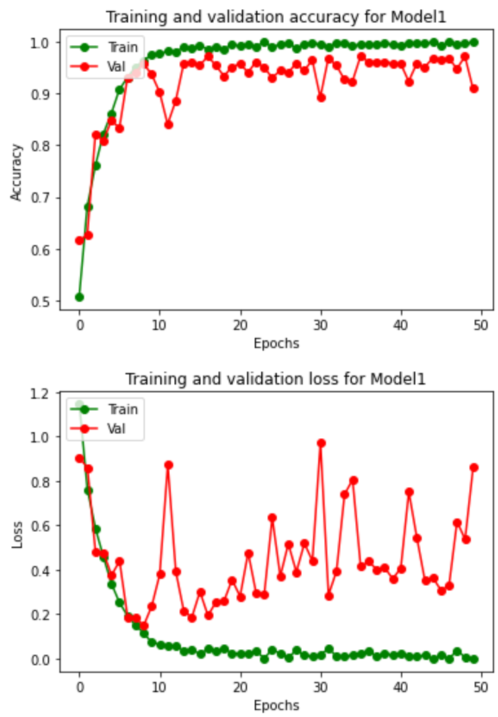

Fig. 4.5.1. Accuracy graph

Fig. 4.5.2. Predicted classes of tumor

ResNet is being put into practice in Keras. The dataset for the detection of brain tumours will be used for this implementation. Both the training folder and the testing folder in this Kaggle project contain MRI data. MRI images of the corresponding tumour classes are organised into four subfolders in each folder. We begin by importing all of the libraries that are required to implement ResNet. Given that this is a medical issue and that mistakes can be extremely expensive, we work to create an automated method for identifying and classifying brain tumours. To train, test, and partition the data, we will use the Sklearn model. ImageDataGenerator has been imported here.

Train and Val datasets are separated in the training folder. Four groups of tumour MRIs are contained in each folder. The epoch rate was set to 50. The dataset file is then unzipped and saved in a predetermined path and folder. A dictionary is explained in relation to data visualisation. Our four classes ('glioma tumor,' "no tumor," "meningioma," and "pituitary tumor") are the dictionary keys. A directory of images is present in each row. The number of photos in each class in the training and testing sets is then counted using an initialised list. We print the total number of photos in each class for the train and test sets.

```
glioma_tumor :
Number of images in Training set = 826
Number of images in Testing set = 100


no_tumor :
Number of images in Training set = 395
Number of images in Testing set = 105


meningioma_tumor :
Number of images in Training set = 822
Number of images in Testing set = 115


pituitary_tumor :
Number of images in Training set = 827
Number of images in Testing set = 74
```

Fig.4.5.3. Dataset count

Visualize one image from each class for the Train set, then save the image information in a designated dataframe. Visualize one image from each class for the Test set, then store the image information in a designated dataframe. There are two train and test folders in the Kaggle dataset. In this case, the train set was divided into train and validation sets. Next, we create a straightforward basic model and run MaxPooling. We put up data generators to process Model 1's data in order to: View the images in our source folders, Feed images to our network along with their labels after converting them to float32 tensors. For the training photos and the validation images, we will each have a separate generator. Our generators will produce batches of 150x150-pixel images along with their labels.

5.CONCLUSION

Being one of the most significant concerns, health issues require proper diagnosis and treatment. Therefore, we suggest a method for categorising brain tumours according to their characteristics. According to a literature review, MRI pictures are the most effective tool for finding brain malignancies. The detection of brain tumours using MRI images requires the use of digital image processing techniques. Different preprocessing techniques are used to reduce noise, clean the image, and change the image. After that, ML algorithms are fed the clean data. Taking the supplied image and classifying it as benign or malignant is the last step.

REFERENCES

[1] Brain Tumor: Statistics, Cancer.Net Editorial Board, 11/2017(Accessed on 17th January 2019)

[2] Brain Tumor Detection Using Convolutional Neural Network Tonmoy Hossain , Fairuz Shadmani Shishir, Mohsena Ashraf MD Abdullah Al Nasim, Faisal Muhammad Shah,2019

[3] Awwal Muhammad Dawud , Kamil Yurtkan, HuseyinOztoprak (2019) "Application of Deep Learning in Neuroradiology: Brain Haemorrhage Classification Using Transfer Learning", Article ID 4629859.

[4] Qiangli, Yingjian Yang, Yingwei Guo,Wei Li , Yang , Hanliu, AND Yan Kang (2021) "Performance Evaluation of Deep Learning Classification Network for Image Features", vol. 9, pp. 9318-9333, 2021.

[5] MortezaEsmaeili, RiyasVettukattil, Hasan Banitalebi, Nina R. Krogh and JonnTerjeGeitung (2021) "Explainable Artificial Intelligence for Human-Machine Interaction in Brain Tumor Localization"Volume11.

[6] Kai Klinker, ManuelWiesche, Helmut Krcmar (2019) "Digital Transformation in Health Care: Augmented Reality for Hands-Free Service Innovation",Inf sys front 22,1419-1431.

[7] Jiawei Lai , Hongqing Zhu, Xiaofeng Ling (2019) "Segmentation of Brain MR Images by Using Fully Convolutional Network and Gaussian Mixture Model with Spatial Constraints", Article ID 4625371.

[8] Asma Naseer, Tahreem Yasir,Arifah Azhar , Tanzeela Shakeel , and Kashif Zafar (2021) "Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI" , Article ID 5513500.

[9] Muhammad Sajjad, Salman Khan, Khan Muhammad, Wanqing Wu, Amin Ullah, Sung WookBaik (2018)"Multi-Grade Brain Tumor Classification using Deep CNN with Extensive Data Augmentation",Volume 30.

[10] Peter Ardhianto , Jen-Yung Tsai, Chih-Yang Lin 3 , Ben-Yi Liau 4, Yih-Kuen Jan ,Veit Babak Hamun Akbari and Chi-Wen Lung (2021) "A Review of the Challenges in Deep Learning for Skeletal and Smooth Muscle Ultrasound Images", volume 11,Issue 9.

[11] RahelehHashemzehi ,Seyyed Javad Seyyed Mahdavi, Maryam Kheirabadi, Seyed Reza Kamel (2020) "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE", Volume 40, Issue 3

[12] Mahmoud khaled Abd-Ellah, Ali Ismail Awad, Ashraf A. M. Khalaf, Hesham F. A. Hamed (2018) "Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural network", J image video.

[13] BijenKhagiand Goo-Rak Kwon (2018) " Pixel-Label-Based Segmentation of Cross-Sectional Brain MRI Using Simplified Seg Net Architecture-Based CNN", Journal of health care engineering, volume 2018, Article ID 3640705.

[14] Nudrat Nida , AunIrtaza , and Muhammad Haroon Yousaf (2021) "A Novel Region-Extreme Convolutional Neural Network for Melanoma Malignancy Recognition", Article ID 6671498.

[15] Emrah Imarak (2021) "Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework", Iran J sci Technal Trans Electrc Eng 45, 1015-1036.

[16] Tobias Hinz, Nicolas Navarro-Guerrero, Sven Maggand Stefan Wermter (2018) "Speeding up the Hyperparameter Optimization of DeepConvolutional Neural Networks", Volume 17.

[17] BijenKhagiand Goo-Rak Kwon (2018) "Pixel-Label-Based Segmentation of Cross-Sectional Brain MRI Using Simplified Seg Net Architecture-Based CNN",Journal of health care engineering, volume 2018, Article ID 3640705.