*Grenze International Journal of Engineering and Technology, Jan Issue*

# Brain Tumor Prediction and Cataloging based on the Medical Resonance Imaging of the Brain using CNN-ResNet

Dr. Gnaneswari Gnanaguru
Ass. Professor, Department of Computer Applications (PG), CMR Institute of Technology, Bengaluru
Email: gnaneswari@yahoo.com

***Abstract*— Today computer vision and image processing with Deep Learning has opened doors to analyse clinical images. This research attempts to classify and predict the malignant tumor presence in the brain. This abnormal growth of the tissue in the brain can be identified from the MRI scan of the patient's brain. Using our model, the images are further classified to identify cancerous or tumorous growth in the brain. The research on Brain MRI was carried out from 2020 onwards with various algorithms and model that can predict the brain-tumor [1]. In the research work I have attempted to improve the accuracy of the model by using a ResNet18 neural network. These networks are complex and requires to be executed using GPU. But the results have shown that it improves the accuracy by more than 7% compared to the other models.**

***Index Terms*— Brain Tumor, MRI, Image processing, computer vision, CNN, ResNet, Deep Learning, TensorFlow, Keras**

## I. INTRODUCTION

Brain-Tumor is diagnosed using medical resonance imaging. The clinicians manually the cancerous growth in the brain using scanned images of the Brain. There are several researches in the past with the 2D Brain MRI images and 3D Brain MRI images. They have used various algorithms for the classification of the cancerous and the non-cancerous brain scan images. The focus of this research is to classify tumorous and non-tumorous brain images using the 2D MRI scans. In this project we used a multilayer CNN along with ResNet18 for improved accuracy using Tensor Flow and Keras for building the model. The model is built using 9 hidden CNN layers along with ResNet18 approach. Thus, compared to the previous study we were able to produce better results[2].

## II. PROBLEM STATEMENT

A model must be designed and built to classify the tumorous and non-tumorous images from the MRI scans with Deep Learning approaches. The dataset used for the research work is available on Kaggle, containing 253 MRI images in total with a classification of 155 malignant and 98 benign tumor.
Apart from the given set of images we have augmented them in a scale of 1550 malignant and 980 benign for normalizing the data and increase the data pool. The data is further divided into training, validation, and test data. In our model 80% were used for training, 10% for testing and 10% for validation. The model basically used a 9 layer CNN which was further built on a ResNet18 since the accuracy was not improving just with CNN.

*Grenze ID: 01.GIJET.10.1.29*


Figure 1. Brain Tumor Dataset Yes/No classes

## III. PREVIOUS STUDIES

Abiwinanda et al. developed a model for brain-tumor classification with CNN which give the accuracy of 98.51% for training and 84.19% for tesintg [3].
Navid et al. provide another multi-class model for brain-tumor classification based on a deep neural network, uses generative adversarial network(GAN) which gives an accuracy of 95.6%.[4]
Mohamed Ali Habib in his model uses CNN with 89% accuracy with test and 91% accuracy with validation data.[5]
In Anand Deshpande's work, the framework's performance is analysed also with super-resolution method and without super-resolution method and has accuracy of 98.14% achieved with super-resolution and ResNet50 architecture. [7]

## IV. METHODOLOGY

The proposed model with CNN-ResNet18 is proposed for the classification. The model is trained with the 'Yes' and 'No' data of the dataset. The novelty of this paper lies in the designing of the REsNet18. The ResNet layer has four residual blocks -- convolutional, batch normalization and pooling. ReLu activation layers followed by the flatten and the dense layer. Such a model is complex than an ordinary CNN and needs GPU systems for processing.

## V. DEEP LEARNING TECHNIQUE

A Convolutional Neural Network is a Deep Learning Neural Network data processing technique[6][7]. It has 3 basic layers the convolutional, pooling and fully connected layer. A rectified Linear Unit(ReLu) uses the function f(k)=max(0,k). In order to reduce the spatial size of the representation, Max pooling layer is used. Batch Normalization helps in arriving with proper initialization of weight. This technique among the best techniques for image capturing and extraction. Feature extraction is a pre-processing technique used on the input data[9][10]. The input layer X of our model has input images of dimensions 240*240*1 and the output Y of the proposed model is the class YES (tumorous) and NO (non-tumorous).
The model has the following layers:

- Input layer
- Zero padding Layer

- 2D Convolutional layer(conv0,conv1,conv2) Layer
- Max pooling layer(maxpool0, maxpool1, maxpool2) Layer
- Batch Normalization(norm0,norm1, norm2) Layer
- ReLu activation function Layer
- ResNet18 – 4 residual blocks after 3 blocks of CNN
- Flatten Layer
- Dense Layer

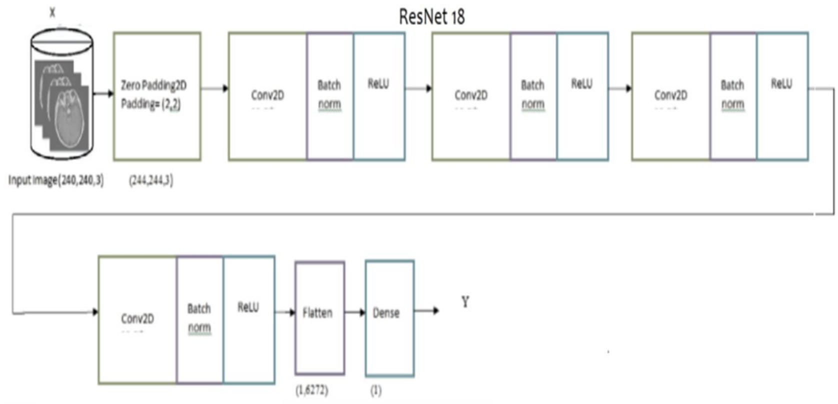


Figure 2 CNN-ResNet Model

Implementation of the model was done by designing the ResNet18 using Tensorflow and Keras API. A total of 25 epochs were used for the learning of the model using training, validation, and testing phases since the accuracy at the $25^{th}$ epoch had very high accuracy. [11][12].

## VI. Model Training

The model that is to be trained uses the 'Adam Optimizer' and the 'binary_crossentropy' for loss function. Relu activation function is used on the dense layer and early checkpoint uses 'keras. callbacks'. The dropout rate is 0.20% [13].

*Details of the Training: (25 Epochs)*

Epoch 1/10
loss: 0.5271 – accuracy: 0.7384
loss: 0.5271 – accuracy: 0.7384 –val_loss: 0.6372 –val_accuracy: 0.6032
Epoch 2/10
loss: 0.5203 – accuracy: 0.7481
loss: 0.5203 – accuracy: 0.7481 –val_loss: 0.5514 –val_accuracy: 0.7452
Epoch 4/10
loss: 0.3674 – accuracy: 0.8388
loss: 0.3674 – accuracy: 0.8388 –val_loss: 0.4659 –val_accuracy: 0.7935
Epoch 5/10
- loss: 0.3107 – accuracy: 0.8664
loss: 0.3107 – accuracy: 0.8664 –val_loss: 0.5760 –val_accuracy: 0.6710
Epoch 6/10
loss: 0.2847 – accuracy: 0.8817
loss: 0.2847 – accuracy: 0.8817 –val_loss: 0.4698 –val_accuracy: 0.7484
Epoch 9/10
loss: 0.2325 – accuracy: 0.9045
loss: 0.2325 – accuracy: 0.9045 –val_loss: 0.3563 –val_accuracy: 0.8710
further training has given the following result after 25 epochs
Epoch 25/25
loss: 0.1164 – accuracy: 0.9599
loss: 0.1164 – accuracy: 0.9599 –val_loss: 0.4151 –val_accuracy: 0.8419

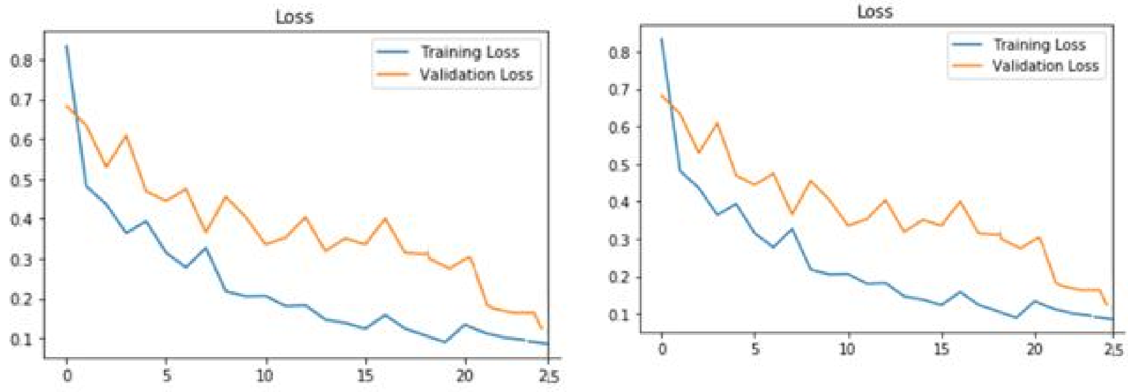


Figure 3. Loss and Accuracy for Training and Validation data

## VII. FINDINGS

The proposed model with CNN-ResNet18 has proved to be the best models so far. The results are 96.20% accuracy for training, 96.12% accuracy for testing and 94% accuracy for Validation. These results are comparatively the best for the given problem.

```
print(f"Test Loss = {loss}")
print(f"Test Accuracy = {acc}")
```

```
Test Loss = 0.16460493206977844
Test Accuracy = 0.9612902998924255
```

```
y_test_prob = best_model.predict(X_test)
f1score = compute_f1_score(y_test, y_test_prob)
print(f"F1 score: {f1score}")
```

```
F1 score: 0.9620253164556962
```

Test

```
y_val_prob = best_model.predict(X_val)
f1score_val = compute_f1_score(y_val, y_val_prob)
print(f"F1 score: {f1score_val}")
```

```
F1 score: 0.9408099968847352
```

Validation

Figure 4. Accuracy of the Model

TABLE I. MODEL COMPARISON [7]

| No. | Models | Accuracy (%) |
|---|---|---|
| **1** | GoogleNet | 74.81 |
| **2** | AlexNet | 82.13 |
| **3** | VGG-16 | 85.37 |
| **4** | Inceptionv3 | 81.85 |
| **5** | **ResNet18** | **96.12** |

## VIII. CONCLUSION

The proposed model has yielded with an accuracy of 96%. This level of accuracy is the highest among the researches based on this dataset [7] [14]. With the intention of increasing the accuracy furthermore ResNet34 and ResNet50 are proposed for the future study for 3D data. The study can also be carried out with the 3D MRI data along with augmentation to increase the data pool.

## REFERENCES

[1] Muhammad Aamir, Ziaur Rahman, Zaheer Ahmed Dayo, Waheed Ahmed Abro, M. Irfan Uddin, Inayat Khan, Ali Shariq Imran, Zafar Ali, Muhammad Ishfaq, Yurong Guan, Zhihua Hu, “A deep-learning approach for brain-tumor classification using MRI images”, Computers and Electrical Engineering,Volume 101,2022,108105,ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2022.108105.

[2] Navoneel Chakrabarty, def me(x), Loaiabdalslam, Dataset accessed on 20th Nov 2022 from https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection, published in 2020.

[3] Abiwinanda N, Hanif M, Hesaputra S T, Handayani A, Mengko T R Brain-tumor classification using convolutional_neural_network. World congress on medicalphysics and biomedical engineering 2018; 2019:183–9.

[4] Ghassemi N, Shoeibi A, Rouhani M. Deep neural network with generative adversarial networks pre-training for brain-tumor classification based on MR images, Biomed Signal Process Control 2020 Mar 1;57:101678.

[5] Mohamed Ali Habib ,Brain Tumor Detection Using Convolutional Neural Networks, accessed on 27th Jan 2023 from https://medium.com/@mohamedalihabib7/brain-tumor-detection-using-convolutional-neural-networks, published on Aug 31, 2019.

[6] Mayank Mishra, Convolutional Neural Networks, accessed on 15 Dec 2022 from https://towardsdatascience.com /convolutional-neural-networks-explained-9cc5188c4939.

[7] Anand Deshpande, Vania V. Estrela, Prashant Patavardhan, The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution, convolutional neural network, and the ResNet50, Neuroscience Informatics, Volume 1, Issue 4, 2021, 100013, ISSN 2772-5286, https://doi.org/10.1016/j.neuri.2021.100013.

[8] Saeedi, S., Rezayi, S., Keshavarz, H. et al. MRI based brain-tumor detection using convolutional deep-learning methods and chosen machine learning techniques, BMC Med Inform DecisMak 23, 16 (2023). https://doi.org/10.1186/s12911-023-02114-6.

[9] Nandita Goyal, Bharti Sharma, Image Processing Techniques for Brain Tumor Identification, 2021 IOP Conf. Ser.: Mater. Sci. Eng. 1022012011.

[10] Saurabh Kumar1, Iram Abid2, Shubhi Garg3, Anand Kumar Singh4, Vivek Jain, Brain-tumor detection using image processing, International Journal of Information Sciences and Application (IJISA). ISSN 0974-2255, Vol.11, No.1, 2019.

[11] Sarkar, S., Kumar, A., Chakraborty, S., Aich, S., Sim, J. S., & Kim, H. C. (2020). A CNN based approach for the detection of brain tumor using MRI scans. Test Engineering and Management, 83, 16580-16586.

[12] M. Gurbină, M. Lascu, and D. Lascu, "Tumor Detection and Classification of MRI Brain Images Using Different Wavelet Transforms and Support Vector Machines," 42nd International Conference on Tel.Comm. and Sig. Processing (TSP), Budapest, Hungary, 2020 "Early Brain Tumor Prediction Using an Enhancement," says Somasundaram SandGobinathR.,2020

[13] H.Ibrahim,A.A.A. Osman, Y.I.Mohamed, MRI brain image classification using neural networks, in Proc. Int. Conf. Comput., Electr. Electron. Eng. (IEEE), Aug.2014,pp.253–258.

[14] T. E. and K. Saruladha, "Design of FCSE-GAN for Dissection of Brain Tumour in MRI," 2020 International Conference on Smart Tech. in Computing, Electrical and Electronics (ICSTCEE), 2020, pp. 1-6, doi: 0.1109/ICSTCEE49637.2020.9276797.