Academy of Engineering

BRAIN TUMOR DETECTION USING CNN AND TRANSFER LEARNING

- Prerna Joshi, Avdhoot Tavhare

ABSTRACT

Brain tumor classification is one of the most important aspects in the fields of medical image analysis. As tumors are regarded as precursor to

cancers, efficient brain tumor classification can prove life saving. For this reason, Convolutional Neural Network(CNN) based approaches are widely being used for classifying brain tumors. CNNs are accustomed to large amount of training data for giving better result. It is where transfer learning comes useful. The models used in our project are have used scratch CNN model, VGG-16, Inception, ResNet.

PROBLEM STATEMENT & **OBJECTIVE**

PROBLEM STATEMENT:

To develop an accurate brain classification system utilizing **Convolutional Neural Networks and** Transfer learning techniques for early diagnosis, improve patient outcomes, and contribute to the field of medical image analysis.

OBJECTIVES:

- · Contribute to healthcare.
- Enhance medical decision-making.
- · Compare model effectiveness.
- · Utilize transfer learning.
- · Improve early detection.

PROPOSED METHODOLOGY

DATA AUGMENTATION: Data Augmentation is a strategy for artificially increasing the quantity and complexity of existing data. The technique is performed for increasing the amount of data to fine-tune the parameters. It is done by adding modifications to our training dataset images by making minor changes, such as flipping, rotation, and

CNN MODEL: The CNN model which we have applied has images of the augmented MRI image data of 48 X 48 pixels, the dataset is split into training, testing, and validation sets. The model consist three convolutional layers, first layer has 64 filters with 3 X 3 kernel, second layer has 128 filters with a 5 X 5 kernel, and third has 512 filters with a 3 X 3 kernel. Each convolutional layer is followed by ReLU activation, MaxPooling, and dropout layers. The model is trained for 200 epochs with a batch size of 64.

VGG-16 MODEL: VGG-16 convolutional neural network is a model which is fine-tuned by freezing some of the layers to avoid overfitting because our dataset is very small. Here images are loaded and resized to a target size of 224 X 224 pixels. Data is split into training, testing and validation sets. VGG-16 model is loaded with weights., the model is trained with 32 batch size for 20 epochs.

ResNet-50:ResNet50 is a 50-layer Residual Network with 26M parameters. Images are resized to a standard size of 224x224 pixels, suitable for the model.

A pre-trained ResNet-50 model with weights from ImageNet is loaded. The model is trained with a batch size of 32 for 20 epochs.

Inception-v3: The Inception network is also a pre-trained network model known as GoogleNet that was introduced by Google in 2014. Here a pretrained InceptionV3 model, with weights trained on ImageNet, is chosen for the transfer learning task. The model is trained using data augmentation with a batch size of 32 for 20 epochs.

COMPARATIVE ANALYSIS

Models and Accuracies:

- Four different models were evaluated for brain tumor classification:
 - CNN from Scratch: Achieved an accuracy of 0.57.
 - VGG-16: Achieved an accuracy of 0.88.
 - o ResNet: Achieved an accuracy of 0.69.
 - Inception: Achieved an accuracy of 0.84.

Model Effectiveness:

0.90

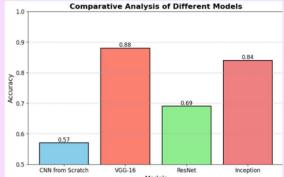
0.85

€ 0.75

0.70

- VGG-16 and Inception models outperformed the other models, achieving significantly higher accuracy rates.
- . The custom CNN from scratch model had the lowest accuracy, highlighting the importance of leveraging pretrained models.

Comparative Analysis of Different Models



Model Selection Consideration:

- · The choice of the classification model should be guided by the specific requirements of the task, dataset size, and available computational resources.
- Transfer learning models can significantly reduce training time and data requirements.

CONCLUSION

In conclusion, the effectiveness of a brain tumor classification model depends on factors like architectural design, pre-training, data quality, and generalization ability. Here, VGG-16 and Inception states higher accuracy than the other models. The choice of model and its subsequent fine-tuning can significantly impact the diagnostic accuracy and, by extension, the potential for early detection and improved patient care in the field of medical image analysis.

FUTURE WORK

Future work in brain tumor classification includes fine-tuning and optimization of models, exploring additional pre-trained models, integrating multi-modal data, enabling real-time deployment, collaborating with healthcare professionals, and addressing ethical considerations. This ongoing research aims to improve model accuracy and applicability in the healthcare domain.

DATASET OVERVIEW

- We experimented on brain tumor MRI images dataset by Navoneel. It consists total of 253 brain MRI
- It includes 155 images of malignant cancer and 98 of benign non-cancerous tumors.
- This dataset consist of two parts yes and no . Yes consists the images detecting brain tumor and no consists of images with no brain tumor
- We split our data into training, validation, and testing. There are 185 images for training, 48 images for validation, 20 for testing to evaluate our model accuracy.







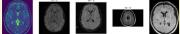












RESULT

Validation Accuracy:

Validation accuracy is a metric used to measure the accuracy of a machine learning model on a validation dataset .Validation accuracy represents the percentage of correctly classified examples in the validation dataset.

• Step Loss:

Step loss (or training loss) typically represents a measure of the model's error during the training process. It is computed as the difference between the model's predicted values and the actual (ground truth) values in the training dataset.

Validation Loss:

Validation loss is similar to step loss but is computed on the validation dataset rather than the training dataset. It measures how well the model is performing on data it has not seen during training.

Model	Val_Accuracy	Step-loss	Val-loss
CNN from Scratch	0.42	4.7	1.03
VGG-16	0.74	0.65	0.63
ResNet	0.80	0.66	0.60
Inception	0.88	0.27	0.31

ACKNOWLEDGEMENT AND REFERENCES

We would like to express our heartfelt gratitude to Sunita Barve Ma'am and Diptee Chikmurge Ma'am for their unwavering support, guidance, and expertise throughout this project. Their invaluable mentorship, dedication, and wisdom have been instrumental in the success of this endeavor. We are truly grateful for their dedication to our growth and their contributions to this research.

REFERENCES:

https://www.aimspress.com/article/id/5701

https://www.researchgate.net/publication/345449977_Brain_Tum or_Classification_With_Inception_Network_Based_Deep_Learning_ Model_Using_Transfer_Learning