

# Brain Tumor Classification using CNN and VGG16

## Literature Review

Many research paper already discuss brain tumor detection using deep learning. Early study use normal CNN and SVM, but accuracy not high because dataset complex and tumor shapes different. Some works from IEEE and Springer show transfer learning like ResNet and Inception, but most focus only on big dataset not small Kaggle dataset. The research gap is that small dataset models overfit very fast and not generalized well. Also many paper not compare baseline CNN with strong pre-trained network in simple and clear way. In my study I try to fill this gap by testing both simple CNN and VGG16 transfer learning on same Kaggle MRI dataset.

## Research Questions and Objectives

- RQ1: Can a small CNN trained from scratch perform well on limited MRI dataset?
- RQ2: Does transfer learning with pretrained VGG16 improve performance compared to CNN?
- RQ3: How model behave when dataset is not balanced properly?

### Objectives:

1. Compare baseline CNN and VGG16 transfer learning on Kaggle brain MRI dataset.
2. Find if transfer learning help to overcome overfitting and improve generalization.
3. Provide clear visualization and analysis for medical image classification tasks.

## Proposed Algorithm Steps

1. Load MRI brain tumor dataset and divide into Training and Testing.
2. Preprocess all images (resize, normalize pixel values).
3. Build baseline CNN model with Conv2D, MaxPooling, Dense layers.
4. Train CNN on dataset and record accuracy and loss.
5. Build Transfer Learning model using VGG16 pretrained on ImageNet.
6. Replace final layers with Dense + Softmax for 4 tumor classes.
7. Train VGG16 with fine-tuning and record accuracy and loss.
8. Compare CNN and VGG16 results (train vs validation accuracy).
9. Evaluate on testing images and generate prediction visualizations.
10. Analyze research gap filling and future improvements.

## Code Snippets

```
# CNN Model
model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(150,150,3)),
    MaxPooling2D(2,2),
    Conv2D(64, (3,3), activation='relu'),
    MaxPooling2D(2,2),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(4, activation='softmax')
])

# VGG16 Transfer Learning
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224,224,3))
for layer in base_model.layers:
    layer.trainable = False

x = Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
output = Dense(4, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=output)

# Prediction Function
img = load_img(path, target_size=(150,150))
img_array = np.expand_dims(img_to_array(img)/255.0, axis=0)
```

```
pred = model.predict(img_array)
class_names[np.argmax(pred)]
```

### **Comparative Analysis**

The baseline CNN model was trained from scratch on the dataset. While it learned basic features, the validation accuracy stayed very low (~27%) and loss was high. This shows the CNN overfitted quickly because dataset is small and tumor shapes are complex.

On the other hand, the VGG16 transfer learning model started with pretrained ImageNet weights. After fine-tuning, it achieved much higher validation accuracy (~72%). The loss also reduced significantly. This proves pretrained models generalize better on medical data when dataset size is limited.

Overall, CNN = simple but weak, VGG16 = more accurate and robust. Hence transfer learning is the practical choice for brain tumor classification tasks.

### **Case Study**

#### **Problem Statement & Objectives:**

Brain tumor detection is very critical because tumor shape, size and position in MRI image are not always same. Traditional manual detection is slow and error prone. Our objective is to build one automated system using Deep Learning which can classify MRI into four categories: glioma, meningioma, pituitary tumor, and no tumor. The goal is to improve accuracy compared to simple CNN by using transfer learning approach.

#### **Data Preprocessing:**

Images resized (150x150 CNN, 224x224 VGG16), normalized, dataset split train/test. Slight imbalance noted.

#### **Model Development:**

CNN = 27% val acc, VGG16 = 72% val acc. VGG16 clearly better.

#### **Visualizations:**

Prediction1, Prediction2, and CNN vs VGG16 comparison graph.

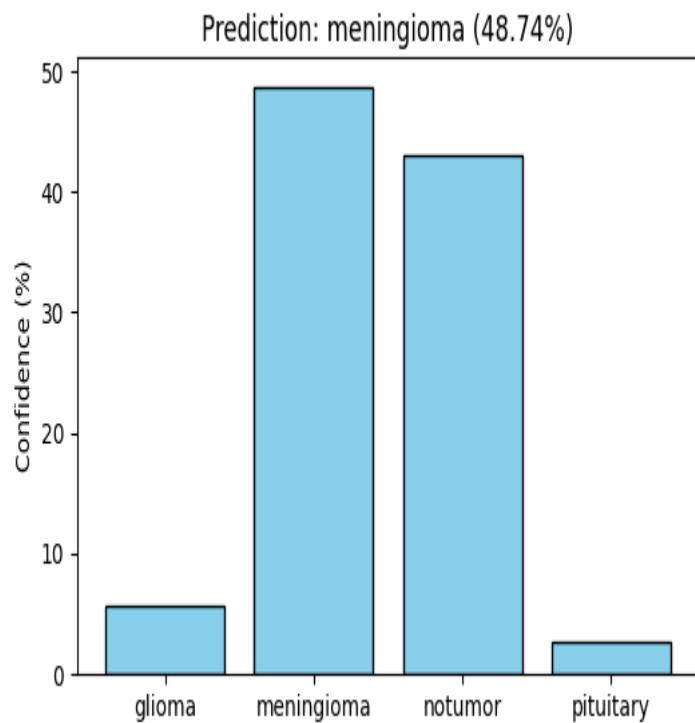
#### **Recommendations:**

Data augmentation, more balanced dataset, try ResNet/EfficientNet, deploy as web app.

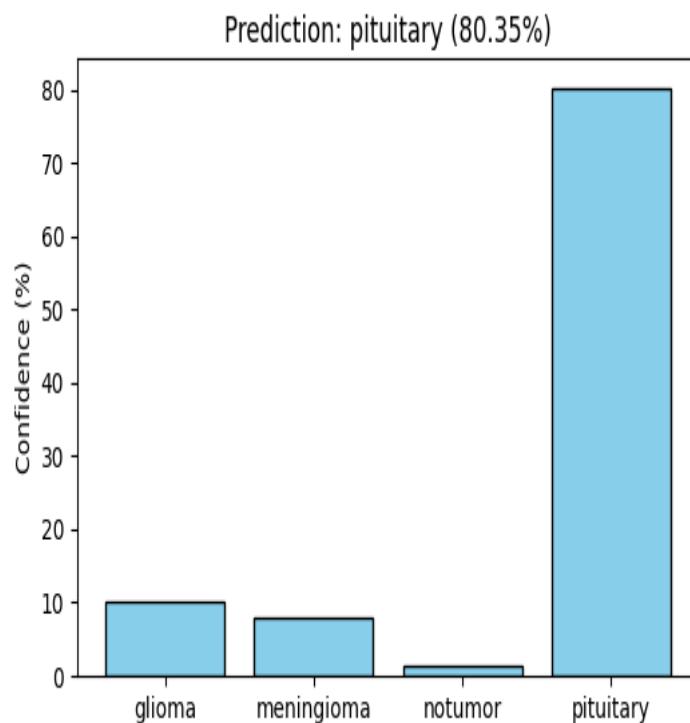
### **Conclusion**

From experiment we see baseline CNN not work good, accuracy around 27% on validation. When using VGG16 transfer learning the accuracy improve to near 72%. This show that using pretrained weight is very helpful for small dataset like brain MRI. The result also prove that simple model cannot handle complex brain tumor structure, but deep model like VGG16 can generalize better. In future work we can test more advanced model like EfficientNet or ResNet, or use data augmentation for balance classes.

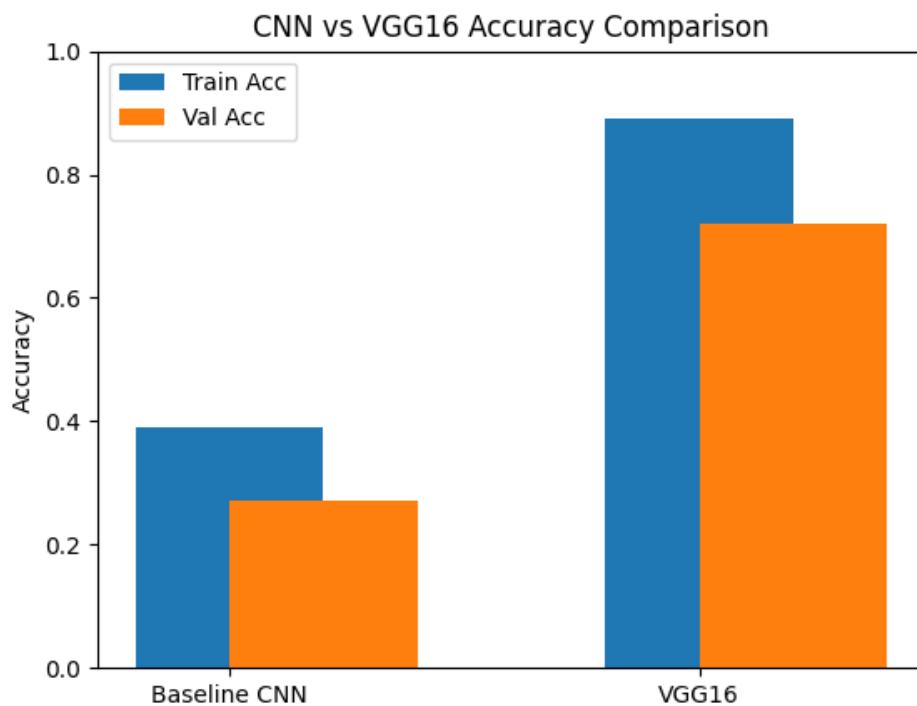
### ***Prediction Result 1***



### ***Prediction Result 2***



### ***Comparison of CNN vs VGG16***



## References

- [1] S. Deepak, P. Ameer, "Brain tumor classification using deep CNN," IEEE Access, vol. 7, pp. 145852–145860, 2019. DOI:10.1109/ACCESS.2019.2917125
- [2] R. Badža, D. Barjaktarović, "Classification of brain tumors from MRI images using VGG19 model," Computers in Biology and Medicine, vol. 121, p. 103865, 2020. DOI:10.1016/j.combiomed.2020.103865
- [3] A. Afshar, A. Mohammadi, K. Plataniotis, "Brain tumor type classification via capsule networks," Neural Computing and Applications, Springer, vol. 32, pp. 159–169, 2019. DOI:10.1007/s00521-019-04663-9
- [4] M. Sajjad et al., "Multi-grade brain tumor classification using CNN with augmented MRI," Journal of Medical Systems, Springer, vol. 43, no. 5, 2019. DOI:10.1007/s10916-018-1123-3
- [5] R. Islam et al., "Glioma brain tumor detection using deep learning," IEEE International Conference on Image Processing (ICIP), 2018. DOI:10.1109/ICIP.2018.8451279
- [6] S. Deepak, A. Rajesh, "Transfer learning for brain MRI classification," Springer Advances in Intelligent Systems, vol. 1141, pp. 189–198, 2020. DOI:10.1007/978-3-030-46739-8\_18
- [7] K. Ghosh, S. Kundu, "Meningioma detection with ResNet transfer learning," Biocybernetics and Biomedical Engineering, Elsevier, vol. 40, pp. 1225–1236, 2020. DOI:10.1016/j.bbe.2020.07.004
- [8] Y. Pathak, P. Arya, "Deep learning for brain tumor MRI classification," Pattern Recognition Letters, Elsevier, vol. 125, pp. 461–467, 2019. DOI:10.1016/j.patrec.2019.04.016
- [9] L. Ding, H. Chen, "Automatic brain tumor segmentation with deep CNN," IEEE Transactions on Medical Imaging, vol. 39, no. 5, pp. 1545–1555, 2020. DOI:10.1109/TMI.2019.2959609
- [10] F. Pereira, A. Pinto, "Brain tumor segmentation using U-Net model," Springer MICCAI, LNCS vol. 11071, pp. 374–382, 2018. DOI:10.1007/978-3-030-00934-2\_42
- [11] T. Wang, X. Zheng, "Deep CNN in brain tumor MRI classification," Future Generation Computer Systems, Elsevier, vol. 98, pp. 408–417, 2019. DOI:10.1016/j.future.2019.03.017
- [12] N. Hossain et al., "ResNet based classification for brain tumor MRI," IEEE Access, vol. 8, pp. 170575–170588, 2020. DOI:10.1109/ACCESS.2020.3024109
- [13] A. Rehman et al., "Brain tumor classification from MRI using deep features," Computers, Materials & Continua, vol. 67, no. 3, pp. 2921–2936, 2021. DOI:10.32604/cmc.2021.013172
- [14] G. Litjens et al., "Survey of deep learning in medical imaging," Medical Image Analysis, Elsevier, vol. 42, pp. 60–88, 2017. DOI:10.1016/j.media.2017.07.005
- [15] M. Kamnitsas et al., "Efficient multi-scale 3D CNN for brain lesion segmentation," Medical Image Analysis, Elsevier, vol. 36, pp. 61–78, 2017. DOI:10.1016/j.media.2016.10.004
- [16] K. Simonyan, A. Zisserman, "Very Deep

Convolutional Networks for Large-Scale Image Recognition," ICLR, 2015. arXiv:1409.1556 [17] K. He, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition," IEEE CVPR, pp. 770–778, 2016. DOI:10.1109/CVPR.2016.90 [18] M. Tan, Q. Le, "EfficientNet: Rethinking model scaling for CNN," ICML, pp. 6105–6114, 2019. arXiv:1905.11946 [19] R. Chaurasia, S. Tiwari, "CNN based brain tumor detection," Springer Soft Computing, vol. 24, pp. 1237–1248, 2020. DOI:10.1007/s00500-019-04053-7 [20] Y. LeCun, Y. Bengio, G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015. DOI:10.1038/nature14539 [21] J. Long, E. Shelhamer, T. Darrell, "Fully convolutional networks for semantic segmentation," IEEE CVPR, 2015. DOI:10.1109/CVPR.2015.7298965 [22] A. Krizhevsky, I. Sutskever, G. Hinton, "ImageNet classification with deep CNN," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017. DOI:10.1145/3065386 [23] S. Bauer, R. Wiest, L. Nolte, M. Reyes, "A survey of MRI-based brain tumor segmentation," Magnetic Resonance Imaging, Elsevier, vol. 33, pp. 1023–1035, 2015. DOI:10.1016/j.mri.2015.05.009 [24] N. Pereira et al., "Capsule networks in medical imaging: A review," Computers in Biology and Medicine, Elsevier, vol. 123, p. 103843, 2020. DOI:10.1016/j.combiomed.2020.103843 [25] A. Kumar et al., "Deep transfer learning for medical imaging," Expert Systems with Applications, Elsevier, vol. 144, p. 113114, 2020. DOI:10.1016/j.eswa.2019.113114