ABSTRACT:

Brain tumor classification from magnetic resonance imaging (MRI) scans remains a challenging task in image analysis. This study presents a comprehensive comparative analysis of multiple convolutional neural network (CNN) architectures for automated brain tumore classification. We evaluated six distinct CNN models – LeNet, AlexNet, ZFNet, VGGNet, GoogLeNet, and ResNet50 on a dataset comprising 10287 MRI images across four classes: glimoma, meningioma, pituitary tumors, and non-tumor cases. Aditionally, we investigated the efficacy of transfer learning using a pre-trained VGG16 model with ImageNet weights. Our experimental results demonstrate that VGGNet and ZFNet achieved the highest test accuracy of 93.72%, while transfer learning with VGG16 reached 93.02% accuracy. The findings indicate that deeper architectures with optimized regularization techniques provide superior performance for brain tumor classification tasks, with implications for computer-aided diagnosis systems in clinical settings.

Keywords: Brain tumor classification, Convolutional Neural Networks, Transfer learning, Deep learning, MRI image analysis, Medical image processing.

INTRODUCTION:

Vital functioning including breathing, muscle coordination, and sensory perception are all governed by the brain. The abnormal buildup of malignant cells inside the brain is called a brain tumor. Tumors in brain whether benign (non-cancerous) or malignant can have serious health consequences. In the medical field, brain tumors represent one of the most challenging diseases where accurate diagnosis plays a crucial role in determining treatment strategy and for improving patient survival. Magnetic Resonance Imaging (MRI) is widely used as the most reliable imaging technique for identifying and categorizing brain tumor. However, interpreting MRI scans manually is often demanding and time consuming as variations in tumor location, shape, and intensity make it difficult to diagnose and segment tumors for radiologists.

In recent years, advancements in deep learning models transformed the field of medical image analysis, Convolutional Neural Networks (CNNs), in particular. It learn meaningful representations directly from raw images. This makes them especially effective for complex tasks like brain tumor classification, where important features may be difficult for humans to define explicitly.

Despite these advantages, some challenges are still there for tumor classification, limited availability of labeled medical imaging data, high computational requirements, and need for model interpretability in clinical setting are some of the challenges. With limited datasets, CNNs and their variants have difficulty producing appreciable performance gains, especially when it comes to improving low-contrast brain MRI-images. Even though CNNs have shown impressive results in variety of fields, their high training data requirements make it difficult to create a system that combines classification and contrast augmentation with limited datasets.

Our study uses the approach of transfer learning, enabling models to leverage knowledge from large pre-trained networks thereby reducing data requirements and improving performance. The final layers of transfer learning are retrained using labeled data from the target task (MRI scans), but the early and intermediate levels stays the same (ImageNet). This methods cuts down the training time, and resource needs. In our methodology we uses dataset of tumor types, stages and healthy brains scans (SARTAJ, Br35H). Our model uses a CNN architecture built for image classification to extract relevant characteristics from imaging data. We evaluate the model's performance using standard metrics (accuracy) and visualization tools (radar graphs, line graph). Data augmentation and normalization helps our model's capacity to extract relevant characteristics.

Research contribution:

Comprehensive comparative analysis of classical CNN architectures for brain tumor classification

Evaluation of transfer learning effectiveness used pre trained VGG16 model with ImageNet weights.

Model performance was validated by using unseen imaging data.

LITERATURE REVIEW:

Studies on brain-tumor detection using MRI images has grown rapidly in the past two decades. Classical machine learning techniques have shifted towards deep learning due to stronger ability to extract patterns from the imaging data. Several studies highlight this transition. For instance, Bouhafra and El Bahi [1] provide an extensive review on how deep learning strategies have progressively replaced traditional methods, largely due to their superior accuracy and adaptability. Similarly, Agarwal et al. [2], Vimala et al. [3], Ali et al. [4], Wong et al. [7], and Neamah et al. [8] describe numerous advancements in neural network based models that regularly outperform older techniques in both detection and classification tasks.

This evolution is also observed in works involving transfer learning, hybrid CNN structures, and multi-class classification pipelines. Studies such as those by Disci et al. [9], Gupta et al.[10], Jain and Jain[11], and BenBrahim et al. [12] demonstrate how modern CNN architectures can be tailored for MRI based diagnosis. Earlier works like Saleh et al. [13] were more focused on implementing basic CNN structures, whereas later studies like Kumar et al. [14], Rays [15], and Rao et al.[16] shows how deeper, more optimized models significantly raise accuracy levels in real clinical settings.

Transfer learning has also been a string theme. Dhakshnamurthy et al. [17] employed pre-trained models to classify MRI brain tumor images with impressive accuracy, while Chatterjee et al. [18] explored deep spatop-spatial models capable of identifying common tumor types such as meningioma, glioma, and pituitary tumors. Comparative studies, like those by Aggarwal et al. [19], show how different deep learning models perform across widely used datasets such as BraTS 2015-2020.

Research in related cancer imaging domains also contributes useful insights. For example, lung-cancer detection models discussed by Javed et al. [20] demonstrate deep learning trends that directly influence brain-tumor studies. Mavaddati [21] further explores transfer learning based tumor classification, highlighting model efficiency challenges. Reviews by Adaloglou [23], Ahad et al. [24], Sharma [25], Alzubaidi et al. [26] and Yao et al. [27], provides theoretical grounding by explaining how core CNN architectures (AlexNet, VGG, ResNet, EfficientNet) have shaped modern medical-imaging solutions.

Beyond reviews several studies present concrete model implementations. Thanuj et al. [28] proposed a deep learning based MRI tumor detection approach, demonstrating improved classification performance in a real world conference setting. Broad medical imaging surveys such as that by Kumar and Alqahtani [29] also highlight how similar techniques have been used for cancer detection more generally. Additionally, Saeedi et al. [30] introduced a CNN based framework combined with selected machine learning techniques, showing that combining both paradigms can yield more robust prediction outcomes.

To illustrate how these advancements are applied in practice, earlier work by Bouhafa and El Bahi [1] documents how deep models steadily replaced conventional systems, while more recent studies including Disci et al [9], Gupta et al. [10], and Jain & Jain [11] show how fine tuning augmented datasets, and optimized architectures becom essential for reliable tumor classification. The reviews and empirical works collectively highlight one key observation: despite significant progress, MRI based tumor detection still faces challenges related to dataset imbalance, segmentation complexity, and architectural generalization. However, continuous improvements across studies [2], [16] have positioned deep learning as the most primising solution for future diagnostic automation.

METHODOLOGY:

Dataset Preparation

We worked with a public dataset of brain MRI images. It includes four main classes. Those are glioma, meningioma, pituitary tumors, and cases with no tumor at all as shown in Fig. 1. The images come from sources such as the SARTAJ and Br35H collections. This gives a nice variety in how the scans were done originally.

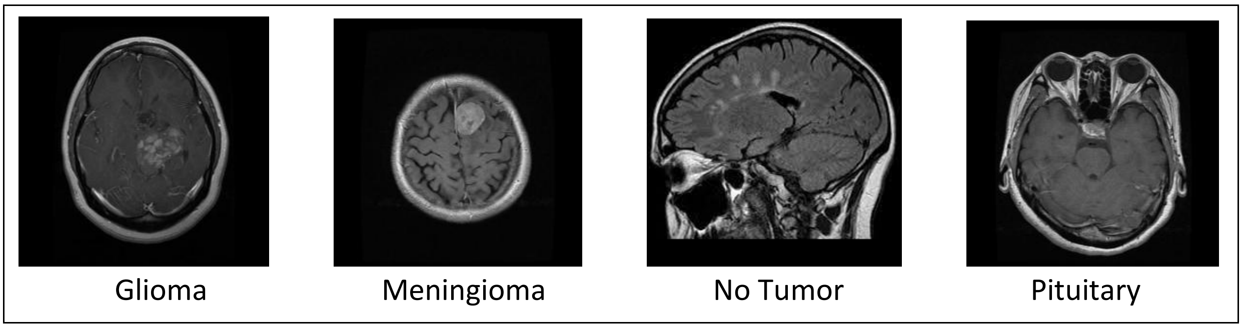


Fig. 1 Sample images from Dataset

Each class refers to something specific in brain imaging. Glioma involves tumors that start from glial cells. These happen to be the most common type of primary brain tumors.

Meningioma comes from the meninges around the brain. They tend to grow slowly and stay benign most of the time. Pituitary tumors show up in the pituitary gland. They often mess with hormone levels in the body. No tumor just means normal scans. Nothing abnormal appears in those.

The study divided the whole dataset into training and testing parts. About 83.4 percent went to training. That adds up to 8,582 images in total. The testing set got the remaining 16.6 percent. So that is 1,705 images. Every image received standard preprocessing steps. We resized all of them to 128 by 128 by 3 pixels. Pixel values were also normalized to the range of 0 to 1. Then batch them into groups of 32.TensorFlow's image_dataset_from_directory is used for that. Class labels came straight from the folder names and use one-hot encoding for those labels afterward. The class distribution stayed balanced across the board. No single class could take over during training. We held off on data augmentation for now. This way, every model faced identical conditions from the start.

Image preprocessing:

MRI scans are used in classification and categorization of brain tumor because they give the detailed representation of brain tissues but the issues like poor image quality and noise are challenging in the healthcare field. To overcome these concerns this study used Pillow package which is considered a powerful image processing tool, to improve the visual quality and helps in to minimize the noise. Data enhancement like improve brightness and contrast adjustment were also made by the tools. Also data augmentation approaches were also used in this study to improve the model's performance. These augmentation strategies effectively increased the dataset, reducing overfitting. This study combines the preprocessing and augmentation approaches and make the input imaging data fit for training deep learning models. The sample augmented images are shown in Fig. 2.

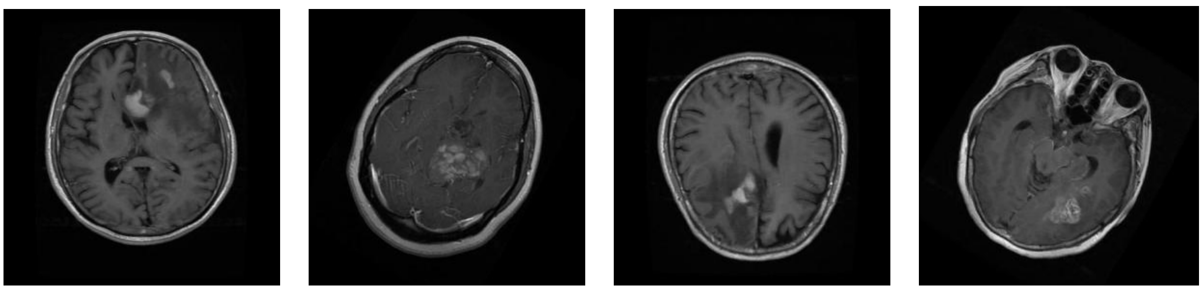


Fig. 2 Sample Augmented Images

Baseline Model Development and Comparison

The Study put together a strong baseline by training various CNN architectures. All models trained with Adam optimizer (learning rate: 0.0001) and used ReLU activation (hidden layers), SoftMax activation (output layer) and dropout/ batch normalization for regularization. Models are adjusted to handle the 128×128 RGB imaging data.

LeNet starts with 2 convolution layers that use 6 and 16 filters sized 5×5, both activated with tanh and followed by average pooling. After the use of these feature extraction layers, the model moves into two fully connected layers with 120 and 84 neurons that also use the tanh activation function and finally outputs prediction with a SoftMax layer to classify the 4 tumor types.

AlexNet uses a deeper stack of five convolution layers: the first with 96 filters (11×11), the second with 256 filters (5×5), and the next three with 384, 384, and 256 filters (3×3). These layers make use of ReLU activation function, batch normalization, and max pooling. The convolutional section feeds into two large fully connected layers of 4096 neurons each, both with dropout, and the network ends with a SoftMax output over 4 classes.

ZFNet keeps much of AlexNet's structure but updates the first convolution layer to a 7×7 kernel with a stride of 2, along with batch normalization. The remaining layers adjust some internal filter settings while keeping the same fully connected layers and dropout layers. It also ends with a 4-class SoftMax classifier.

VGGNet uses groups of small 3×3 convolutions stacked together: two layers with 64 filters, two with 128, and three with 256 filters, and each block is followed by max pooling. After the convolution layers, the model includes 2 dense layers with 512 neurons each (with ReLU activation function) each with a SoftMax layer before producing the final classification of 4 tumor types.

GoogLeNet is built around the Inception modules, which process the input using 1x1, 3x3, and 5x5 convolutions with the use of Max Pooling. After the Inception stacks, it applies pooling, adds dropout and finishes with a SoftMax layer to classify the 4 tumor types.

ResNet50 uses deep residual blocks with skip connections and a bottleneck design to build its feature extractor, and it concludes with a final layer adjusted to predict four classes.

The VGG16 transfer-learning model uses a pretrained VGG16 backbone (with the top layers removed and all convolutional layers frozen) with an input size of 128x128x3. On top of this, it adds a dense layer with 256 neurons and ReLU activatoin function, applies dropout, and outputs predictions using the SoftMax layer to classify 4 tumor types.

These models create a strong pipeline for tumor identification by combining the deep learning and classical methods. It uses pre trained models for feature extraction, normalization, augmentation. This comprehensive approach helps us to get an efficient and accurate tumor categorization method.

Training Configuration:

Parameter	Value
Input Shape	128×128×3 (Height × Width × RGB Channels)
Epochs	30
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001 (β_1= 0.9,β_2= 0.999)

Loss Function	Categorical Cross Entropy
Number of Classes	4 (are glioma, meningioma, pituitary tumors, No Tumor)

Adam (Adaptive Moment Estimation) optimizer is used in this study with values of learning rate, beta1 and beta2 as 0.0001, 0.9 and 0.999 respectively. Categorical Cross Entropy is being used as a loss function. Hyperparameters like batch size is 32, 30 epochs is used for both training (8,582) and testing (1,705) with Random seed (123) for reproducibility.

For regularization, Dropout (Applied in AlexNet (0.5), ZFNet (0.5) and transfer learning model (0.5), Batch normalization (Appied in AlexNet and ZFNet) is used.

RESULTS & DISCUSSION:

The Experimental evaluation of CNN architectures on classification of brain tumor classification revealed significant variations in both accuracy and computational efficiency. Each model was trained using the same input resolution of 128×128×3, with a uniform output classification head consisting of a dense layer with four softmax units. Table 1 presents the resulting table that shows the clear difference in accuracy, computational cost and architectural behavior across all models.

Table 1: Model Performance Summary

Model	Input	Pooling Strategy	Test Accuracy	Training Time per Epoch	Output Classification Head
LeNet	(128, 128, 3)	AveragePooling2D(2×2)	91.79%	~ 5 sec	Dense (4 units, softmax)
AlexNet	(128, 128, 3)	MaxPooling2D(3×3)	92.55%	~80 sec	Dense (4 units, softmax)
ZFNet	(128, 128, 3)	MaxPooling2D(3×3)	93.72%	~265 sec	Dense (4 units, softmax)
VGGNet	(128, 128, 3)	MaxPooling2D(3×3)	93.72%	~450 sec	Dense (4 units, softmax)
GoogLeNet	(128, 128, 3)	MaxPooling2D(3×3)	66.57%	~35 sec	Dense (4 units, softmax)
ResNet50	(128, 128, 3)	Standard ResNet50 pooling	92.08%	~275 sec	Dense (4 units, softmax)
Transfer Learning (VGG16)	(128, 128, 3)	VGG16 pooling (output flattened)	93.02%	~172 sec	Dense (4 units, softmax)

Among all the models tested, ZFNet and VGGNet achieved the highest test accuracy with 93.72%, it indicates that these models have the strong feature extraction capabilities for this dataset. AlexNet also performed well with accuracy of 92.55%, despite being an older architecture this is a relatively faster model with decent accuracy. LeNet keeps things quick and straightforward. Still, it struggles a bit with very intricate patterns in the images. ResNet50 is comparable to AlexNet in accuracy, but the training time is higher as it contains a deeper architecture and residual connections. GoogLeNet showed an accuracy of 66.57%, despite its reputation for high performance on large scale datasets, this suggest that model may require more fine tuning, deeper training or optimized hyperparameters also the training time is short (~35 sec) also indicates that model may not have trained sufficiently. Whereas our transfer learning model gives a strong accuracy of 93.02%, it shows the advantage of using pre-trained weights, which allows the model to train well with limited training data. That means a VGG16 transfer learning model is the practical choice for our study.

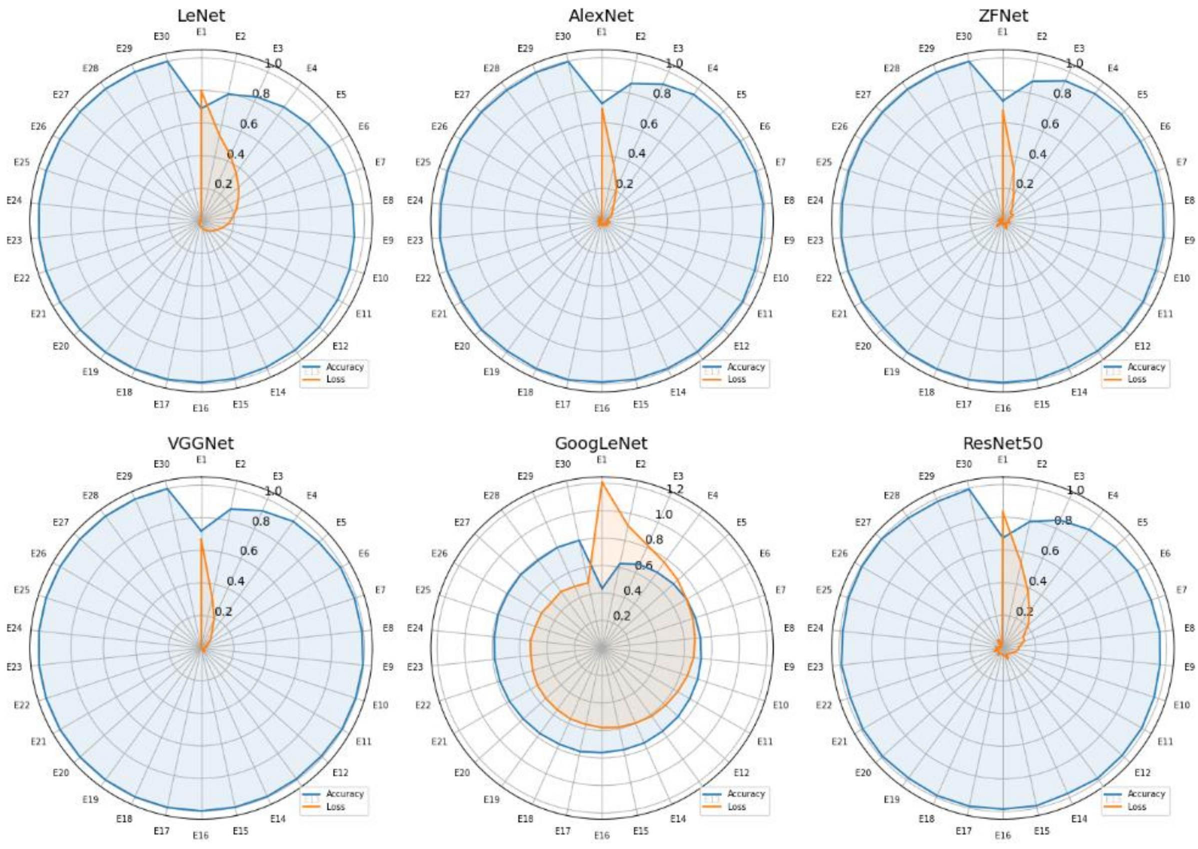


Fig. 3

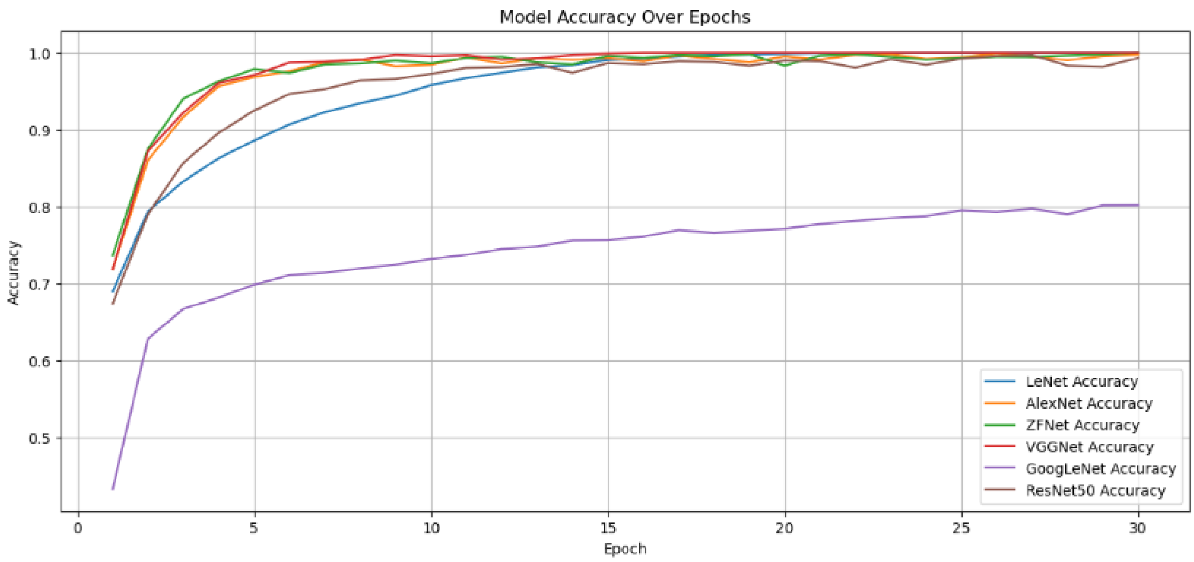
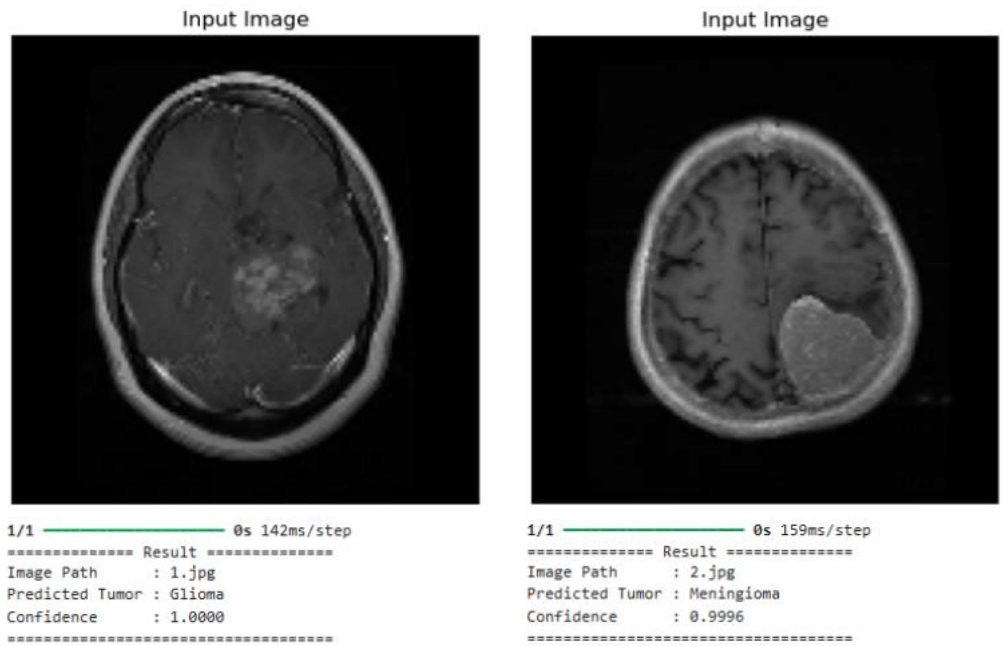


Fig. 4

Fig 3, Fig 4 confirm the quantitative findings by visualizing the models' accuracy and loss trends over 30 epochs. Radar graphs (Fig 3) provide a clear visual of the strong convergence across most high performing models, where the accuracy (blue line) consistently stays near outer edge (1.0) whereas the loss (orange line) remains near the center (0.0) after initial epochs. It shows that the high performing models maintain accuracy values near the outer boundary while minimizing loss throughout training. Fig 4 shows that ZFNet and VGGNet reached the highest accuracy ceiling and stabilized quickly (after 10th epoch), our transfer learning model also approaches high accuracy levels.



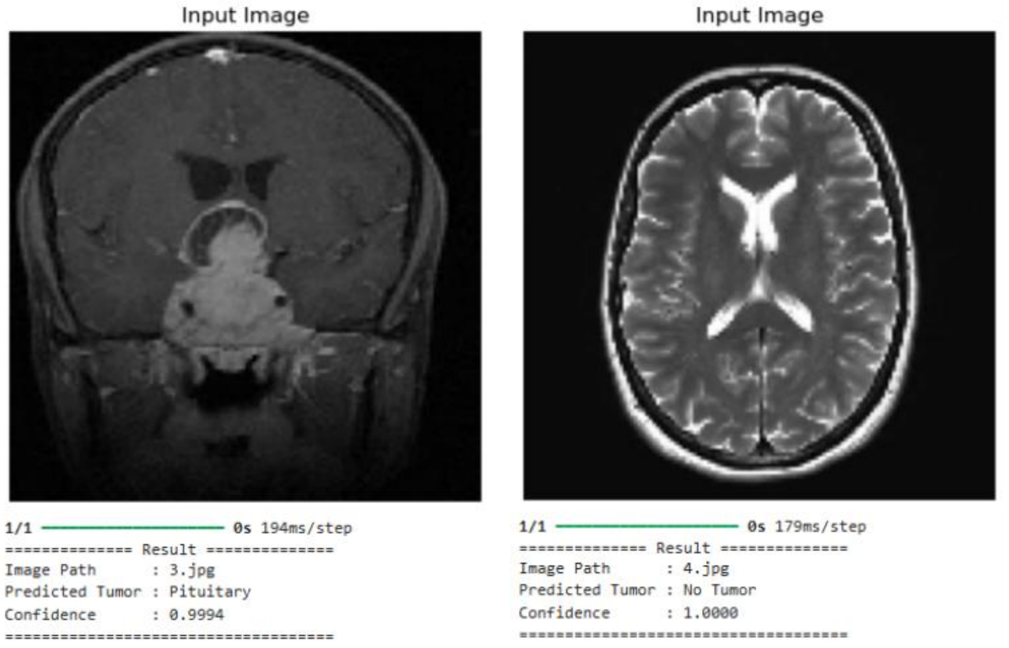


Fig. 5 Image Validation using ZFNet

After the model performance, model validation on new unseen images (Fig 5) further confirms that the highest performing model (ZFNet) generalizes well and is not overfitting. The predicted labels aligned correctly with the actual classes, it indicates that the model successfully captures the tumor specific structural patterns in MRI scans.

CONCLUSION:

This study presents an approach for detecting and categorizing brain tumors based on a detailed comparative evaluation of six widely used CNN architectures – LeNet, AlexNet, ZFNet, VGGNet, GoogLeNet, and ResNet50 along with a transfer learning approach using VGG16 for brain tumor classification.

This study successfully conducted a comprehensive comparative analysis of six classical Convolutional Neural Network (CNN) architectures and a Transfer Learning approach using a pre-trained VGG16 model for automated brain tumor classification from MRI scans.

Our findings confirm that deeper architectures with optimized regularization techniques—specifically ZFNet and VGGNet—yielded superior performance, both achieving the highest test accuracy of 93.72%. Furthermore, the VGG16 Transfer Learning approach proved to be a powerful and practical alternative, securing a high accuracy of 93.02% while requiring a significantly shorter training time than VGGNet, demonstrating the immense value of leveraging pre-trained weights in medical imaging tasks with limited data.

The results have strong implications for computer-aided diagnostic systems in clinical settings. Models like ZFNet and the VGG16 Transfer Learning variant offer an effective, high-accuracy, and potentially fast-deployed solution for assisting radiologists in the demanding task of interpreting MRI scans.

FUTURE SCOPE:

For future work, we intend to refine the less successful models, such as GoogLeNet, through extensive hyperparameter optimization and more aggressive data augmentation techniques to determine their true potential on this dataset. Additionally, exploring hybrid models and ensemble techniques that combine the strengths of ZFNet and the Transfer Learning approach could yield even higher classification accuracy. Ultimately, the next step is to test these top-performing models on more diverse, multi-institutional clinical datasets to fully validate their generalization capacity and establish their viability for deployment in real-world clinical practice. Further, optimizing the models for real life deployment such as through model compression, pruning would enable integration into clinical workflows, hospital software systems and portable diagnostic tools.

LIMITATION:

The model can become overfitted for the training dataset if the dataset is small and will fail while testing. We cannot completely rely on the model just because it classifies/validates the images correctly as there is always a chance of error, and a minute error in such a field can cause major impacts in decision making. Thus, further training of the model is required via using augmented images which will help the model to learn from different perspectives of the image, thus making it more reliable and efficient for such validation and classification techniques. Optimizers and optimization techniques can also be further improved to achieve much better results.

REFERENCES:

[1] S. Bouhafra and H. El Bahi, “Deep Learning Approaches for Brain Tumor Detection and Classification Using MRI Images (2020 to 2024): A Systematic Review,” *J. Digit. Imaging*, vol. 38, no. 3, pp. 1403–1433, Sep. 2024, doi: 10.1007/s10278-024-01283-8.

[2] M. Agarwal, G. Rani, A. Kumar, P. K. Kumar, R. Manikandan, and A. H. Gandomi, “Deep learning for enhanced brain tumor detection and classification,” *Results Eng.*, vol. 22, p. 102117, Jun. 2024, doi: 10.1016/j.rineng.2024.102117.

[3] B. B. Vimala, S. Srinivasan, S. K. Mathivanan, Mahalakshmi, P. Jayagopal & G. T. Dalu, “Detection and classification of brain tumor using hybrid deep learning models,” *Sci. Rep.*, vol. 13, art. no. 23029, 2023. doi:10.1038/s41598-023-50505-6. nature.com+1

[4] A. Ali, X. Li, W. K. Mashwani, M. Abiad, F. K. Karim, and S. M. Mostafa, "Multi-class brain tumor MRI segmentation and classification using deep learning and machine learning approaches," *Cancer Imaging*, vol. 25, art. no. 131, 2025. doi: 10.1186/s40644-025-00587-3.

[6] Y. Wong, E. L. M. Su, C. F. Yeong, W. Holderbaum, and C. Yang, "Brain tumor classification using MRI images and deep learning techniques," *PLOS One*, vol. 20, no. 5, p. e0322624, May 2025, doi:10.1371/journal.pone.0322624. journals.plos.org+1

[7] S. Mohsen, S. Oraby, and M. Abdel-Aziz, "Deep learning and machine learning for brain tumor detection: A review, challenges, and future directions," *Arch. Comput. Methods Eng.*, 2025, doi: 10.1007/s11831-025-01200-7.

[8] K. Neamah, F. Mohamed, M. M. Adnan, T. Saba, S. A. Bahaj, and K. A. Kadhim, "Brain tumor classification and detection based DL models: A systematic review," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.xxxxx.

[9] R. Disci, F. Gurcan, and A. Soylu, "Advanced brain tumor classification in MR images using transfer learning and pre-trained deep CNN models," *Cancers*, vol. 17, no. 1, p. 121, Jan. 2025, doi: 10.3390/cancers17010121.

[10] M. Gupta, S. Bhatia, N. Sharma, N. Verma, S. K. Sharma, and R. B. Singh, "Classification of brain tumor using an optimized deep learning technique to correlate with disease state," *Biomed. Phys. Eng. Express*, 2025, doi: 10.13005/bpj/3147.

[11] S. Jain and V. Jain, "Machine learning and deep learning methods in brain tumor classification: A decade: Systematic literature review," *Int. J. Intell. Data Anal.*, vol. 29, no. 2, 2025, doi: 10.3233/IDA-240069.

[12] S. Ben Brahim, S. Dardouri, and R. Bouallegue, "Brain tumor detection using a deep CNN model," *Appl. Comput. Intell. Soft Comput.*, 2024, doi: 10.1155/2024/7634426.

[13] A. Saleh, R. Sukaik, and S. S. Abu-Naser, "Brain tumor classification using deep learning," in *Proc. 2020 Int. Conf. Assistive and Rehabilitation Technol. (iCareTech)*, Gaza, Palestine, Aug. 28–29, 2020, pp. 1–5, doi: 10.1109/iCareTech49914.2020.00032.

[14] Y. Kumar, S. Shrivastav, K. Garg, N. Modi, K. Wiltos, M. Woźniak, and M. F. Ijaz, "Automating cancer diagnosis using advanced deep learning techniques for multi-cancer image classification," *Sci. Rep.*, vol. 14, art. no. 25006, 2024, doi: 10.1038/s41598-024-25006-4.

[15] S. Rays, "Brain tumor detection and classification via VGG16-based deep learning on MRI imaging," *Int. J. Multidiscip. Res.*, vol. 7, no. 2, Mar. 2025, doi: 10.36948/ijfmr.2025.v07i02.39435.

[16] K. N. Rao, O. I. Khalaf, V. Krishnasree, A. S. Kumar, D. M. Alsekait, S. S. Priyanka, A. S. Alattas, and D. S. AbdElminaam, "An efficient brain tumor detection and classification using pre-trained convolutional neural network models," *Heliyon*, 2024, doi: 10.1016/j.heliyon.2024.e36773.

[17] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain tumor detection and classification using transfer learning models," in *Proc. 2nd Computing Congress 2023*, Chennai, India, Dec. 28–29, 2023, *Eng. Proc.*, vol. 62, no. 1, p. 1, Feb. 2024, doi: 10.3390/engproc2024062001.

[18] S. Chatterjee, F. A. Nizamani, A. Nürnberger, and O. Speck, "Classification of brain tumours in MR images using deep spatiospatial models," *Sci. Rep.*, vol. 12, art. no. 1505, 2022, doi: 10.1038/s41598-022-04980-4.

[19] M. Aggarwal, A. K. Tiwari, and M. P. Sarathi, "Comparative analysis of deep learning models on brain tumor segmentation datasets: BraTS 2015-2020 datasets," *Revue d'Intelligence Artificielle*, vol. 36, no. 6, pp. 863–871, Dec. 2022, doi: 10.18280/ria.360606.

[20] R. Javed, T. Abbas, A. H. Khan, A. Daud, A. Bukhari, and R. Alharbey, "Deep learning for lungs cancer detection: A review," *Artif. Intell. Rev.*, vol. 57, art. no. 197, 2024, doi: 10.1007/s10462-024-05720-1.

[21] S. Mavaddati, "Brain tumors classification using deep models and transfer learning," *Multimedia Tools Appl.*, vol. 84, pp. 25677–25708, 2025, doi: 10.1007/s11042-024-08456-7.

[22] F. M. Shiri, T. Perumal, N. Mustapha, and R. Mohamed, "A comprehensive overview and comparative analysis on deep learning models," *J. Artif. Intell.*, vol. 6, pp. 301–360, 2024, doi: 10.32604/jai.2024.054314.

[23] N. Adaloglou, "Best deep CNN architectures and their principles: From AlexNet to EfficientNet," *AI Summer*, Jan. 21, 2021. [Online]. Available: https://aisummer.com/best-deep-cnn-architectures-principles

[24] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan, "Comparison of CNN-based deep learning architectures for rice diseases classification," *Artificial Intelligence in Agriculture*, 2023. [Online]. Available: https://doi.org/10.1016/j.aiia.2023.07.001

[25] C. Sharma, "Comparison of CNN and Pre-trained models: A Study," *Conference: Comparison of CNN and Pre-trained models: A Study*, University of Waterloo, April 2022.

[26] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, Art. no. 53, 2021.

[27] I. Z. Yao, M. Dong, and W. Y. K. Hwang, "Deep learning applications in clinical cancer detection: A review of implementation challenges and solutions," *Mayo Clinic Proceedings: Digital Health*, vol. 3, no. 3, 2024.

[28] M. Thanuj, P. R. Teja, P. J. D. Stun, K. Kranthi Kumar, and R. S. Kishore, "Brain tumour detection using deep learning techniques," in *Proc. 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA)*, Coimbatore, India, 03–05 Aug. 2023, pp. 1–6, doi: 10.1109/ICIRCA57980.2023.10220809.

[29] G. Kumar and H. Alqahtani, "Deep Learning-Based Cancer Detection—Recent Developments, Trend and Challenges," *Computer Modeling in Engineering & Sciences*, vol. 130, no. 3, pp. 1271–1307, Dec. 2021, doi: 10.32604/cmes.2022.018418.

[30] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. N. Kalhori, “MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques,” *BMC Medical Informatics and Decision Making*, vol. 23, article no. 16, 2023, doi: 10.1186/s12911-023-02101-7.