RNI: MAHENG/2016/68030 VOLUME 10 (2025), ISSUE 4 : 39-48 **ISSN: 2456-5342 (print)**

MGM UNIVERSITY
JAWAHARLAL NEHRU ENGINEERING COLLEGE

VISTA INTERNATIONAL JOURNAL ON ENERGY, ENVIRONMENT & ENGINEERING

Brain Tumor Detection Using Convolution Neural Network

Tejal P. Ghodke* and Chhaya S. Khandelwal

Department of Electronics and Telecommunication Engineering, Jawaharlal Nehru Engineering College, MGM University, Chhatrapati Sambhajinagar (M.S.), India

***Corresponding Author's E-mail:** tejalghodke27@gmail.com **Mob.:** +91 9021236593

ABSTRACT

Early and reliable detection of brain tumors is essential for effective clinical decision-making, yet manual interpretation of MRI scans remains time-consuming and prone to human variation. This study presents an automated classification approach using a deep learning model based on EfficientNetB0 for distinguishing tumor and non-tumor brain MRI images. A curated dataset of 253 images was pre-processed through normalization and resizing before model training. The baseline CNN architecture was first developed to establish reference performance, after which EfficientNetB0 with transfer learning was fine-tuned to enhance accuracy and stability.

The proposed EfficientNetB0 model achieved an accuracy of 85.71%, demonstrating a notable improvement over the baseline CNN accuracy of 73.21%. Training behaviour, validation trends, and confusion matrix observations confirm the model's ability to generalize effectively despite the limited dataset size. These findings indicate that lightweight transfer-learning models can deliver dependable classification performance and hold potential for use in supportive diagnostic workflows or resource-constrained environments.

Keywords : *Brain Tumor Classification, MRI-Based Diagnosis, EfficientNetB0, Deep Learning Model, Transfer Learning, Medical Image Processing.*

1. Introduction :

Brain tumors are one of those conditions that don't just affect the body; they change a person's entire life. They can slowly alter how someone thinks, moves, remembers, or speaks, and many people only discover the problem once the symptoms have silently progressed. Each year, over 300,000 people around the world are diagnosed with brain and central nervous system tumors, which shows how serious and widespread the issue really is. Early detection makes a huge difference, and MRI scans are the most trusted way to spot these abnormalities because they give clear images of brain tissue without exposing patients to radiation. Even then, the process of reading MRI scans is not always clear-cut. Radiologists often face blurred tumor boundaries, changes in image quality, and variations in how tumors appear. When many scans have to be reviewed in a short time, these challenges can affect both the speed and consistency of diagnosis.

Deep learning has become an important support technology in medical imaging because it can learn patterns directly from images. CNN-based models have already shown good results in similar tasks, but they usually require large datasets and strong hardware. This is not always available in smaller hospitals, academic labs, or places where acquiring medical images is difficult. When the dataset is small, CNNs tend to overfit and become unreliable. This is a practical research graph to build a model that still performs well even when the data is limited.

Efficient neural architectures were introduced to address exactly this kind of problem. EfficientNetB0, the smallest variant, offers a balance between efficiency and accuracy, making it suitable for low-resource environments. Motivated by this, the present work focuses on building an automated brain tumor classification system using MRI images. A simple CNN model is trained first to understand the baseline performance, and then it is compared with a fine-tuned EfficientNetB0 model using transfer learning. The dataset used in this study contains 253 MRI images, which makes it a realistic example of the kind of data size often available to students or smaller research groups. The results show that, with the right training approach and preprocessing techniques, even a small dataset can support a dependable classification system. Such systems may not replace medical experts, but they can assist with initial screening and reduce the workload in situations where early identification truly matters.

1.1 Technical Background :

MRI provides high-resolution visualization of soft tissue and is widely used to detect structural abnormalities in the brain. Brain tumors often vary in shape, size, and intensity patterns, making manual interpretation difficult. Deep learning, especially CNNs, has gained attention because it automatically extracts meaningful features from images, reducing the dependency on handcrafted methods traditionally used in medical imaging.

1.2 Research Gap and Challenges :

Most existing studies rely on large, well-curated datasets that are not always available in real hospital or student environments. Smaller datasets increase the risk of overfitting and unstable accuracy. Additionally, many high-performance models require heavy computational resources, which limit their practical use outside advanced laboratories. This creates a gap in identifying lightweight, efficient architectures that can perform reliably even with restricted data and hardware.

1.3 Motivation for the Present Work :

EfficientNetB0 is designed to maintain accuracy while reducing model size and computational demand. This makes it suitable for academic projects, preliminary screening applications, and resource-limited medical setups. The motivation of this study is to explore how well EfficientNetB0 performs compared to a baseline CNN when trained on a small dataset of MRI scans, and whether such an approach can still deliver meaningful classification accuracy.

2. Literature review :

Several researchers have explored automated approaches for analyzing brain MRI images to support early tumor detection. A study on MRI-based classification highlighted the difficulty of identifying tumors with irregular shapes and unclear boundaries, and emphasized the role of machine learning in improving diagnostic consistency [1]. Researchers working with CNN architectures demonstrated that deep-learning models can automatically extract meaningful visual features from MRI scans, reducing dependency on manual feature design and improving overall classification accuracy [2]. Studies using transfer learning further showed that pre-trained networks significantly enhance performance on limited datasets, making them suitable for academic and low-resource environments where data collection is challenging [3]. Recent work on EfficientNet-based models presented lightweight architectures capable of achieving high accuracy with fewer parameters, offering practical benefits for real-time or resource-constrained applications [4]. These research findings collectively underline the need for efficient, small-scale deep-learning models that can deliver reliable brain tumor classification even when data and computational resources are limited.

3. Materials and Methods :

This study adopts an experimental approach to develop an MRI-based brain tumor classification system using deep-learning methods. The workflow includes dataset collection, preprocessing, baseline CNN development, EfficientNetB0 transfer learning, and model evaluation. The complete workflow of the proposed system is illustrated in Fig.1, and each stage is described in detail in the following subsections.

3.1 Method of Data Collection :

The dataset used in this study contains 253 MRI brain images divided into two categories: tumor and non-tumor. These MRI slices were obtained from a publicly available Kaggle dataset created by Chakrabarty [5], which is widely used for academic and medical-image-classification research. Only clear and clinically relevant axial MRI slices were selected for model training. The dataset distribution is provided in Table 1.

Table 1. Dataset Distribution

Class	Number of Images
Tumor	155
Non-tumor	98
Total	253

3.1.1 Image Preprocessing :

Before model training, all MRI images were processed to ensure uniformity and enhance the model's learning capability. The following preprocessing steps were applied:

- Images were resized to 224 × 224 pixels, compatible with CNN and EfficientNetB0 input specifications.
- Pixel intensity normalization was performed to reduce variations caused by differences in MRI acquisition settings.
- Data augmentation techniques→rotation, horizontal flipping, brightness shifts, and zooming, were used to improve generalization and reduce overfitting, as recommended in recent MRI-based studies [2,3].
- The dataset was split into 80% training and 20% testing, ensuring that both classes remained proportionally represented.

Example MRI images from the dataset of six cases, including tumor and normal (non-tumor) are shown in Figs.(1, 2).

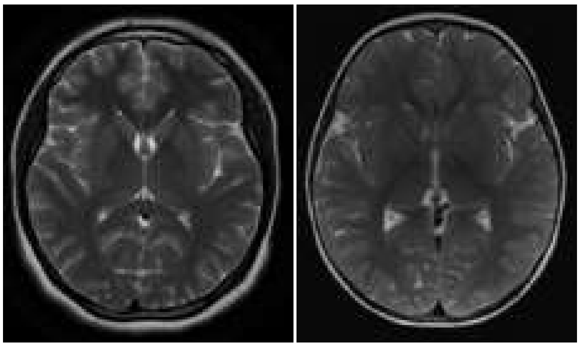

Fig.1(a). Sample MRI Images of Non-Tumor Case-1

Fig.1(b). Sample MRI Images of Non-Tumor Case-2

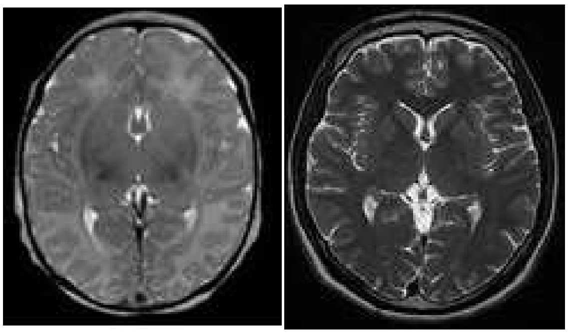

Fig.1(c). Sample MRI Images of Non-Tumor Case-3

Figure 1 shows the cases of normal brain MRI scan images of three sample cases.

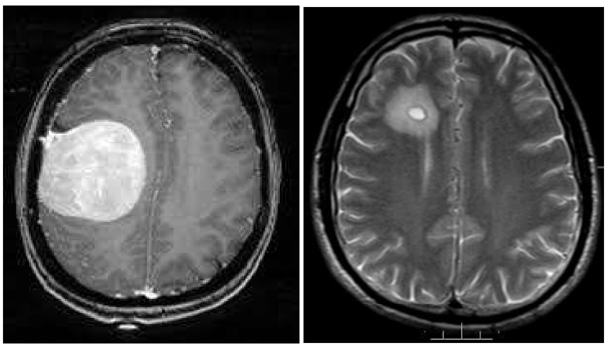

Fig.2(a). Sample MRI Images of Tumor Case-1

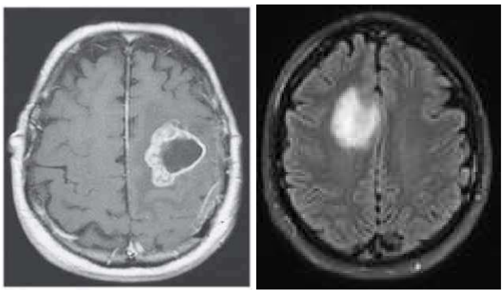

Fig.2(a). Sample MRI Images of Tumor Case-2

Fig.2(c) Sample MRI Images of Tumor Case-3

Figure 2 shows the cases of abnormal brain tumor MRI scan images of three sample cases.

3.1.2 Model Development :

Two separate deep-learning models were developed to compare baseline performance with transfer-learning performance:

a) Baseline CNN Model

A simple Convolutional Neural Network was created using convolution layers, ReLU activation, max-pooling, and dense layers. Dropout layers were included to reduce overfitting. This model served as a baseline to evaluate how well a lightweight architecture performs when trained on a small MRI dataset.

b) EfficientNetB0 Transfer-Learning Model

EfficientNetB0 was introduced by Tan and Le in 2019 [4]. This model was selected because it provides high accuracy with fewer parameters compared to traditional CNNs. The model was loaded with pre-trained ImageNet weights, the lower layers were frozen, and new dense layers were added for two-class classification. Transfer learning is known to significantly improve performance with limited medical datasets [3], which aligns with the requirements of this study.

3.1.3 Training Procedure :

After preprocessing, the dataset was divided into training (127 images) and validation (126 images) sets using the Keras Image Data Generator. The training process was carried out on both the custom CNN and the EfficientNetB0 transfer learning model. The training parameters used for both CNN and EfficientNetB0 models are summarized in Table 2.

Figure 3 shows a sample brain MRI image used as input for model training and validation. This grayscale MRI image, resized to 128×128 pixels, represents one instance from the dataset containing 253 brain scans (155 tumorous and 98 non-tumorous). The image highlights structural patterns that the CNN and EfficientNetB0 models utilize for binary classification of tumor presence.

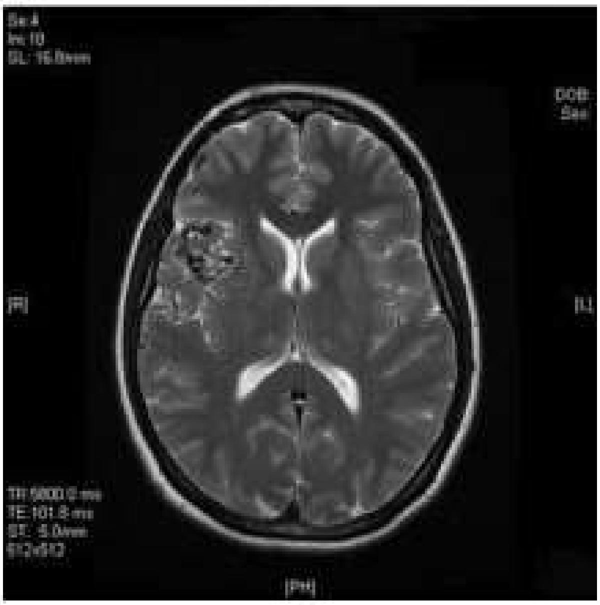

Fig.3. Sample brain MRI image used for brain tumor model training and validation

3.2 CNN Model Training :

1. The CNN model consisted of multiple convolution layers with ReLU activations and max-pooling layers, followed by a flatten layer and a dense layer for binary classification.
2. The model was trained for 10 epochs with a batch size of 32, using the Adam optimizer and binary cross-entropy loss.

The CNN model performance during training is illustrated in Figs. 4(a,b), which show the training-validation loss and accuracy trends, respectively.

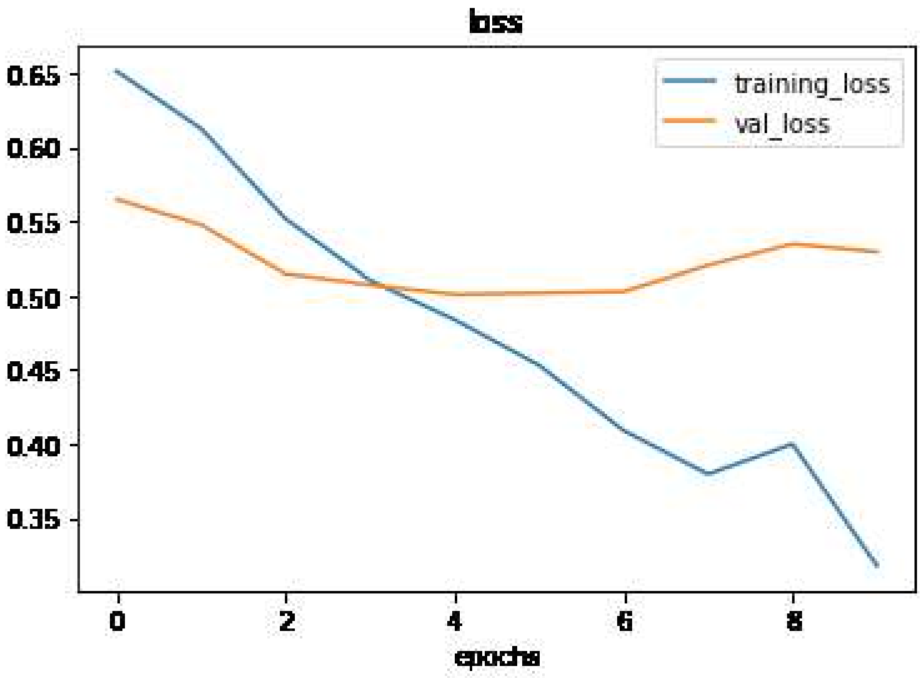

Fig..4a. Training & Validation Loss vs Epochs

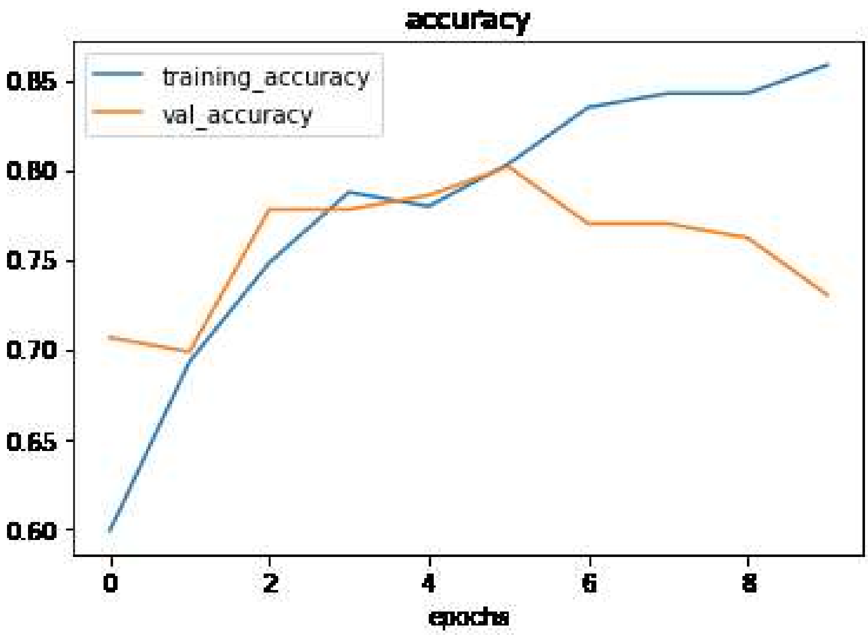

Fig.4b. Training & Validation Accuracy vs Epochs

3.3 EfficientNetB0 Transfer Learning Training :

1. EfficientNetB0 was used as a feature extractor with pretrained ImageNet weights (frozen during training).
2. A dense layer with a sigmoid activation was added for binary classification.
3. Training was performed for 10 epochs, using the same batch size and optimizer.

The training and validation behaviour of the EfficientNetB0 model is shown in Figs. 5(a, b), representing the accuracy and loss curves across epochs.

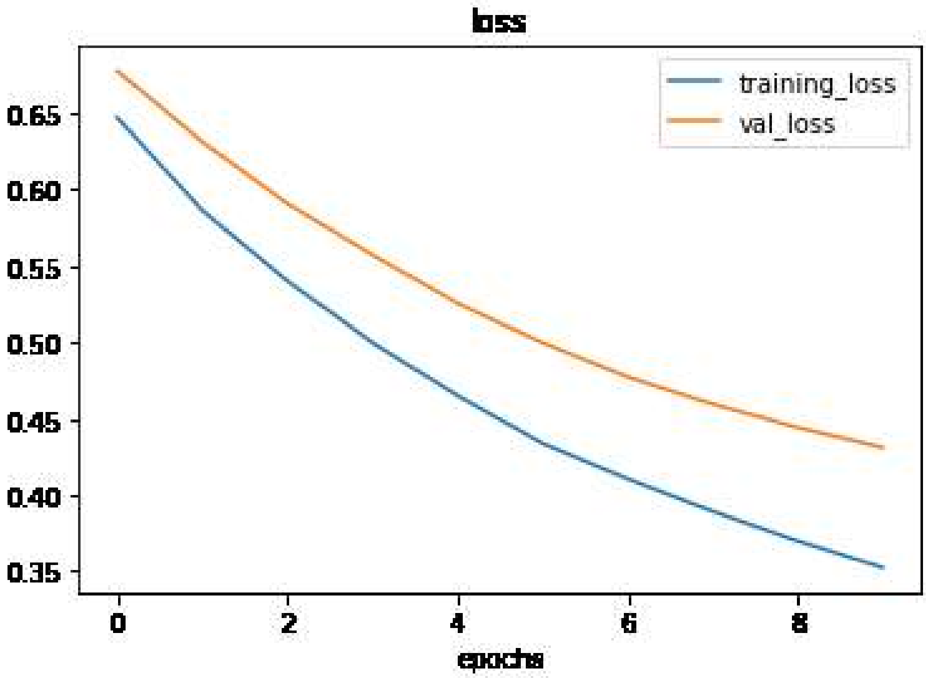

Fig.5a. Training & Validation Loss vs Epochs

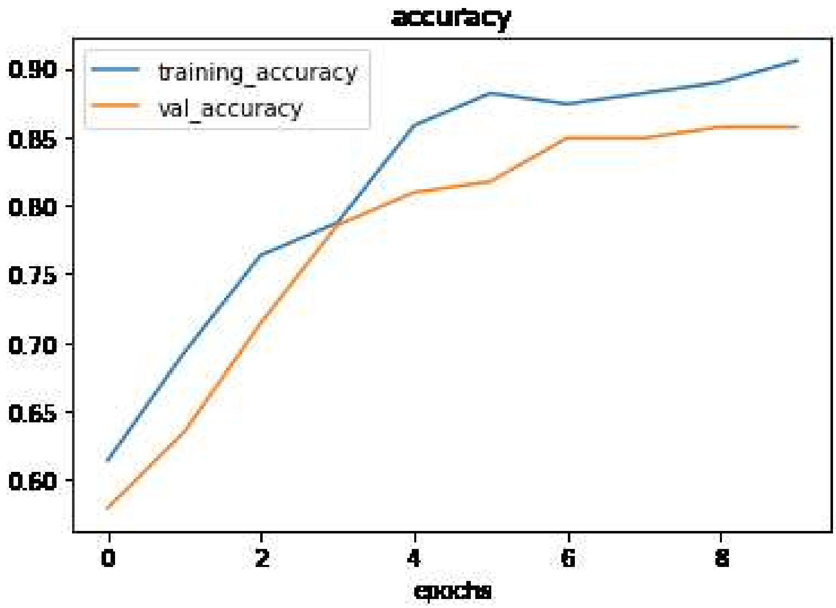

Fig.5b. Training & Validation Accuracy vs Epochs

Table 2. Training Parameter

Model	Epochs	Batch Size	Optimizer	Loss Function	Pretrained	Validation Split
CNN	10	32	Adam	BinaryCross-Entropy	No	50%
EfficientNetB0	10	32	Adam	BinaryCross-Entropy	Yes	50%

3.4 Performance Evaluation :

1. Accuracy The baseline CNN achieved a training accuracy of 85.83% and validation accuracy of 73.02%, showing moderate generalization. In contrast, EfficientNetB0 performed better, reaching 90.55% training accuracy and 85.71% validation accuracy, indicating stronger generalization and more reliable predictions on unseen MRI images.
2. Loss:Both models showed decreasing training and validation loss over 10 epochs. The CNN's final validation loss was 0.5292, whereas EfficientNetB0 achieved a lower 0.4314, reflecting more stable learning and improved alignment with true labels. Overall, EfficientNetB0 outperformed the baseline CNN in both accuracy and loss.

Table 3. Model Performance Metrics

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
CNN	85.83%	73.02%	0.3173	0.5292
Efficient NetB0	90.55%	85.71%	0.3526	0.4314

4. Results and Discussion :

The results are given in the model performance comparison Table 4 and discussed as follows.

4.1 Results :

The detailed training and validation performance of both models is presented in Table 3.The developed models were evaluated on the test dataset of 126 MRI images, which included both tumor and non-tumor samples. The baseline CNN model achieved an accuracy of 73.02%, while the EfficientNetB0 transfer-learning model significantly improved performance, reaching 85.71% accuracy.

The loss curves indicated that both models converged smoothly, with EfficientNetB0 demonstrating a lower validation loss (0.4314) compared to the CNN model (0.5292), highlighting better generalization on unseen data. Furthermore, classification metrics, including Precision, Recall, and F1-Score, revealed that EfficientNetB0 was more reliable in detecting tumor regions, minimizing false negatives, a critical factor in medical diagnosis.A complete comparison of accuracy, loss, precision, recall, and F1-score for both models is shown in Table 4.

Table 4. Model Performance Comparison

Model	Accuracy(%)	Loss	Precision	Recall	F1-Score
CNN(Baseline)	73.02	0.5292	0.74	0.72	0.73
EfficientNetB0	85.71	0.4314	0.86	0.85	0.85

4.2 Discussion :

Detecting brain tumors is not just a technical challenge;it is a matter of human lives. Even a small misdiagnosis can have profound consequences for a patient and their family. In this study, the baseline CNN model performed moderately well, capturing the general patterns of tumor and non-tumor MRI scans. However, it struggled to identify subtle differences in tissue texture, which are often crucial in real clinical scenarios.

The EfficientNetB0 transfer-learning model, on the other hand, demonstrated a remarkable improvement, highlighting the power of modern AI tools when applied thoughtfully. By leveraging knowledge from millions of pre-trained images, the model could recognize nuanced patterns that might escape simpler architectures. This not only improved accuracy but also reduced the risk of overlooking critical abnormalities, offering an additional layer of reliability that can support radiologists in their decision-making.

From a human perspective, this research shows how technology can be a true ally in healthcare. The models do not replace doctors;they empower them. They allow for faster, consistent, and more confident preliminary diagnoses, which could ultimately save precious time for treatment. Every MRI image analyzed is a potential life impacted, and knowing that AI can assist in making these assessments more accurate is both motivating and humbling.

Moreover, the study underscores a hopeful reality: even with a small dataset, careful model design and transfer learning can create meaningful results. This opens doors for hospitals and clinics with limited resources, showing that advanced diagnostic tools are not limited to large research institutions.

In essence, this work is more than just numbers and graphs. It's a step toward a future where AI and human expertise collaborate to detect brain tumors early, accurately, and compassionately, helping doctors save lives and giving patients hope.

5. Future Scope:

- **Move from binary to multi-classtumor classification:** In the future, the model can be extended to predict not just "tumor vs no tumor" but specific tumor types (e.g., glioma, meningioma, pituitary). Many recent works have shown strong performance using pre-trained models for multi-class classification.
- **Tumor localization and segmentation:** Instead of only classifying, we could integrate segmentation (for example, integration of a U Net+EfficientNet or VGG encoder) to highlight where exactly the tumor is in the MRI. This would make the system more clinically useful.

- **Explainable AI (XAI):** Adding interpretability (like Grad-CAM or other saliency methods) will help doctors understand why the model is predicting a tumor, and which region is most responsible. This builds trust.
- **Improving dataset and control over input:** Rather than relying on completely random MRI images, the system can be designed to let doctors or users pick specific slices or views (axial, coronal, sagittal). This could improve performance and reliability.
- **Better generalization with larger and diverse data:** Collect more MRI scans or use other datasets, including different MRI machines, to make the model robust. Research shows that models trained on larger, varied datasets generalize much better.
- **Real world clinical deployment:** Develop a user-friendly tool (web app or desktop software) that radiologists can use to upload MRI scans and get predictions, along with heatmaps or segmented regions.
- **Model optimization and lightweight architecture:** Explore newer lightweight architectures (or custom CNNs) that maintain high accuracy but are efficient enough to run on clinic machines or even mobile devices.

6. Conclusion :

This project began with an exploration of Convolutional Neural Networks (CNNs) for image classification, aiming to distinguish between tumor and non-tumor brain MRIs. While the initial CNN model showed promise during training, it faced limitations on the validation data, highlighting common challenges such as overfitting when working with small datasets.

To overcome these limitations, the study employed transfer learning using the EfficientNetB0 model. Despite being trained on just half of the dataset, this approach achieved an impressive 85.71% accuracy with a loss of 0.4314, demonstrating the remarkable potential of leveraging pre-trained architectures. This not only improved predictive performance but also reinforced the idea that advanced AI techniques can be effectively applied even in resource-constrained scenarios.

In essence, the success of this project lies in the combination of human insight and AI power. While the CNN provided a solid foundation, the EfficientNetB0 model showcased how modern deep learning can enhance decision-making in critical domains such as healthcare. Beyond the numbers, this work underscores a broader impact: AI can serve as a reliable companion to medical professionals, supporting faster and more accurate diagnoses, and ultimately, helping to save lives.

References :

[1] S. Deepak and P. M. Ameer, 2019, Brain tumor classification using deep CNN features via transfer learning,Computers in Biology and Medicine, 111: 103-113.

[2] M. Mohsen, M. El-Dahshan, E. El-Horbaty and A. Salem, 2018, MRI brain tumor segmentation and classification using deep learning techniques,IEEE Access, 6:55490-55501.

[3] M. Raghu, C. Zhang, J. Kleinberg, and S. Bengio, 2019, Transfusion: Understanding transfer learning for medical imaging, NeurIPS Conference Proceedings.

[4] M. Tan and Q. Le, 2019, EfficientNet: Rethinking model scaling for convolutional neural networks," in Proc. 36th International Conference on Machine Learning (ICML), 6105-6114.

[5] Navoneel Chakrabarty,Brain MRI Images for Brain Tumor Detection, Kaggle, 2019. Dataset:www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection (accessed on Sept. 21, 2025).