# An Explainable and Optimised Framework for Brain Tumor Detection Using EfficientNet-B4 with attention

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# An Explainable and Optimised Framework for Brain Tumor Detection Using EfficientNet-B4 with attention

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**Abstract**

Brain tumor classification aims to identify and differentiate various types of tumors from MRI scans to aid in early diagnosis and treatment. Traditional methods, including manual examination by radiologists and basic machine learning models, often struggle with high inter-observer variability, limited scalability, and low accuracy due to the complex nature and variability in tumor shapes and all. These limitations highlight the need for automated, reliable, and interpretable systems. In this study some models used CNN, VGG16, EfficientNet-B4, and EfficientNet-B4 enhanced with an attention mechanism to classify brain MRI images. Two popular optimization techniques, ADAM and SGD are employed to compare learning performance, where ADAM offers faster convergence with adaptive learning rates, and SGD provides more stable generalization. Both optimizers were tested across all models to analyze their impact. Experimental results demonstrate that the EfficientNet-B4 model with attention and the ADAM optimizer achieves the best classification performance. Additionally, Explainable AI using LIME is integrated to highlight important image regions influencing predictions, making the model more transparent and suitable for clinical use.

Keywords: Brain Tumor Classification, MRI Imaging, Explainable AI (LIME), EfficientNet-B4

# 1 Introduction

## 1.1 Motivation

Brain tumors are among the most life-threatening conditions affecting both children and adults Lutz et al. (2022). Traditional diagnostic approaches which trust on manual interpretation of MRI scans Chotzoglou (2022). In many developing regions, the lack of specialized professionals and advanced diagnostic tools makes it even more challenging to ensure timely and accurate tumor detection. The advancement of Artificial Intelligence, particularly deep learning, offers a transformative opportunity to automate and improve diagnostic precision. By developing an intelligent and explainable system for brain tumor classification, this research aims to contribute to faster, more reliable, and accessible diagnostic support. The motivation is not only technical but also humanitarian to bridge the gap between advanced healthcare technologies and real-world clinical needs, especially in under-resourced areas.

## 1.2 Aim of the study

The main aim of this study is to design DL-based classification system for detecting and categorizing brain tumors from MRI images. This system utilizes a range CNN models including CNN, VGG16, and EfficientNet-B4, along with attention mechanisms, to enhance diagnostic accuracy. By incorporating two optimization strategies ADAM and SGD the study also aims to evaluate model performance under different training dynamics. Additionally, the study integrates Explainable AI (LIME) to provide interpretability and transparency to the classification results, thereby making the system more trustworthy for clinical use. A secondary aim is to deploy this system through a user-friendly Flask-based web interface, ensuring it is accessible to healthcare professionals for real-time use.

## 1.3 Research Questions

There are some research question for this study:

1. How accurately can DL models classify different types of brain tumors from MRI images?
2. Which optimization technique (ADAM vs SGD) provides better performance in training DL models for medical image classification?
3. How can explainable AI techniques (like LIME) be integrated to improve the interpretability and trustworthiness of automated brain tumor detection?

## 1.4 Objectives of the Research

The research objectives for this report are:

1. To develop and train multiple DL models (CNN, VGG16, EfficientNet-B4, EfficientNet-B4 with Attention) for brain tumor classification.
2. To compare the impact of two optimization techniques ADAM and SGD on model accuracy, convergence, and training time.

## 1.5 Outline of the Report

This report is structured into the following sections:

**Chapter 1: Introduction** This chapter introduces the research problem, motivation, aim, research questions, and objectives. It sets the foundation for the study by discussing the importance of early and accurate brain tumor diagnosis and how deep learning can offer effective solutions in this domain.

**Chapter 2: Literature Review** This chapter reviews existing research in the area of brain tumor diagnosis. It outlines traditional diagnostic approaches, their limitations, and the evolution toward intelligent systems using ML and DL. Various past methodologies, models, and performance comparisons are critically analyzed.

**Chapter 3: Research Methodology** This chapter describes the CRISP-DM methodology adopted in the study. It details each phase business understanding, data understanding, data preparation, modeling, evaluation, and deployment. It also covers dataset details, preprocessing techniques, data visualization, and class balancing using SMOTE.
**Chapter 4: Design Specification** This chapter presents the system design, including the overall architecture, frameworks and tools used, the proposed model functionality, and the integration of Explainable AI (LIME).
**Chapter 5: Implementation** This chapter explains the practical implementation of the models: CNN, VGG16, EfficientNet-B4, and EfficientNet-B4 with Attention. It discusses how each model was built, trained, and fine-tuned using both ADAM and SGD optimizers.
**Chapter 6: Evaluation** This chapter analyzes the experimental results. It includes confusion matrices, accuracy scores, and comparative performance of models using SGD and ADAM optimizers.
**Chapter 7: Conclusion and Future Works** This chapter concludes the report by summarizing key findings and contributions. It also discusses the limitations of the current study and proposes directions for future research, including the use of more advanced models.

# 2 Related Work

## 2.1 Traditional Diagnosis and its Limitations

Traditional research showed that MRI is highly important in brain tumor diagnosis as it can give clear images of the inside of the brain without causing harm Mittal and Tayal (2021). Most doctors rely on MRI scans because they clearly display both common and unusual tissues in the brain. In a traditional manner, doctors trained in radiology or neurology check the scans simply by looking for signs such as tumors using different characteristics such as shape, size, texture and position Hussain et al. (2022). Though clinicians trust this method, it has some drawbacks that can reduce the accuracy and speed of diagnosis. Besides, tumors usually have irregular shapes, blend with normal tissue and may grow slowly in a way that is tricky to see with the naked eye when the tumor is just starting to develop Bisoyi (2022).

The analysis of MRIs takes a lot of time as well. A brain scan can give hundreds of different images, all of which must be examined with care. Such a situation increases the mental responsibility for doctors and also slows down the process of diagnosing, mainly in cases where many patients are being treated. Often, in several developing countries and rural areas, it is difficult to find trained radiodiologists or neurologists for interpreting MRI results. The absence of experts can cause delays in the correct diagnosis, errors in understanding the problem and fewer possibilities for success in treatment or planning surgery Politi et al. (2022). Patients in areas with poorly developed healthcare often have to wait a long time for their scans to be examined which could result in them missing an early chance for treatment.

## 2.2 Evolution of Brain Tumor Diagnosis: From Manual to Intelligent Systems

In the past, brain tumor diagnosis relied on manual methods, but now it is done with the help of today's advanced technology and data Khalighi et al. (2024). At the beginning, all diagnosis was based on physical checks, assessments of nerves and medical images produced with CT and MRI. Back then, physicians used X-ray and CT scanning to detect any unusual changes or growths in the brain with more accuracy than before. Still, most of the process relied on skilled radiologists using their eyes to look at the scans, compare these cases with past records and decide on a diagnosis Ivy et al. (2023). The development of CAD in the early 2000s greatly changed things for the field Hunde et al. (2022). The use of handcrafted elements of brain scans such as shape, brightness and texture, gives ML models the ability to separate tumor types Kibriya et al. (2023). Even though there was an increase in automated diagnosis, the use of machine-generated features made it difficult for the models to perform well and apply to different tasks.

## 2.3 ML in Brain Tumor Detection

Islam et al. (2020), a model that uses K-means clustering and an improved SVM classifier was offered to detect by processing images from MRI. It addresses the rising difficulty at an early stage which is vital as it may help save people's lives. The first step is to carry out an MRI scan and then a median filter is applied to enhance the quality of the images during preprocessing. Following the refined image, K-means clustering separates the image into parts related to the infection and finally, the ISVM classifier is used to find abnormal growths like tumors.

Bhagat and Kaur (2022), they suggested a combined method for brain tumor classification where K-means clustering is first used for segmentation, SGHO helps in segmentation too, SURF gathers the tumor features needed and the final step is classification by means of an SVM. By using Contrast-Enhanced MRI, the study tries to enhance how confidently brain tumors can be spotted for medical diagnosis. SGHO handles both selection of segments and choice of important features, so that only the useful ones enter into the actual classification step. The approach gave excellent results with a 99.24% accuracy, 95.83% precision and 95.30% recall, much better than other approaches.

Sarkar et al. (2020) there is a brain tumor detection process which was suggested using MRI which handles things with a SVM. The study's utmost goal is to determine the nature of brain tumors by examining their characteristics found on MRI images. It starts with enhancing the image, segmenting the area with tumor, taking out important details and then detecting the tumor using an SVM classifier.

Maqsood et al. (2022), experts designed an advanced and computerized system for brain tumor detection and classification based on MRI images to help radiologists make early and accurate decisions and avoid errors. The reason for this research is the serious disease and the insufficiencies of the usual way of diagnosing brain cancer. The suggested approach includes these five tasks: linear boosting of edges, identifying tumors by a hand-made 17-layer deep network, feature extraction using a changed MobileNetV2, optimal feature extraction with an entropy-based method and classification of meningioma, glioma or pituitary tumors by an M-SVM.

Ansari et al. (2020) is to use an approach based on analysis for discovering and classifying brain tumors due to the lengthy and complicated process of manual diagnosis. The study works to increase by blending different image and machine learning methods. Noise is removed by using morphological operations and wrecked areas are identified by applying DWT to improve results and reduce computations. The SVM classifier is next used to separate the MRI images based on the features that have been extracted. The proposed system worked very well, with an accuracy rate of 98.91%, showing it could be trusted for diagnosis.

Sutradhar et al. (2021) talked about how automated brain tumor detection and classification is difficult since tumor shapes, locations and MRI image characteristics vary a lot. The aim of the study was to check and compare various methods. Several trained models based on DL were used and the emphasis was given to their classification accuracy, the amount of computation they required and energy consumption during training. Among the tested models, EfficientNet-B3 was the most effective and gave an accuracy rate of 98.16%, higher than both other deep learning networks and regular machine learning methods. It shows that EfficientNet-B3 is a capable and reliable choice for identifying brain tumors.

Archana and Komarasamy (2023) suggested an automated method to identify and classify brain tumors to solve MRI diagnosis problems such as lengthy processing times, inaccurate findings and dealing with variable tumor sizes. This study tries to streamline and enhance the way medical images are segmented and classified. Tests revealed that the approach is more accurate than existing methods at telling whether a brain tissue is normal or pathological, achieving a classification rate of 97.7%.

Kumar et al. (2021) introduced an automatic system for diagnosing and grouping brain tumors on MRI images. This research deals with the problems of background noise in MRI images and the difficulty in correctly separating tumor locations. The suggested way follows four important steps: preprocessing, feature extraction, classification and segmentation. In order to make the image clearer, Median Filter is first used to remove noise.

Sankaranayaanan et al. (2023) proposed challenges of diagnosing and treating brain tumors arise due to privacy issues when all data is collected in one place. Instead of traditional ways that only one central server gathers data, this study introduced federated learning which trains models while also protecting data privacy. A CNN model influenced by the VGG16 architecture was employed in the research to spot brain tumors from MRI images. The main aim was to adjust the parameters of the model so it could correctly identify brain tumors in the federated environment. The outcomes of the tests prove that FL-based approach provides better results, at an accuracy of 92%.

Tripathy et al. (2023) introduced a way to detect brain tumors that uses transfer learning with the EfficientNet models (EfficientNet-B2, B3 and B4). The goal of this study was to make tumor classification from MRI images more accurate by handling the problems of small dataset size and the need for a big model. They increased the performance of training by using steps such as resizing, cropping and data augmentation on the images. With its method for scaling depth, width and resolution, EfficientNets were able to seize complex features more successfully than ResNets which needed users to scale them manually.

Zhaputri et al. (2021) proposed a DL-based solution for brain tumor classification using the EfficientNet architecture accurately diagnosing glioma, meningioma, and pituitary tumors through automated classification. The motivation behind the study lies in the complexity and time-consuming nature of manual diagnosis, which is highly dependent on expert experience. The proposed approach utilized transfer learning with various versions of EfficientNet, particularly focusing on EfficientNet-B1 and EfficientNet-B2, which demonstrated superior performance with an accuracy of 96%.

Table 1: Summary Table

| **Study** | **Proposed Approach** | **Strengths** | **Weaknesses** | **Results** |
|---|---|---|---|---|
| Islam et al. (2020) | Hybrid K-means clustering + Improved SVM (ISVM); median filter preprocessing; MRI segmentation and classification | Efficient execution; high specificity; good balance of speed and accuracy | Tested only on pre-collected datasets; untested on higher-dimensional features and diverse datasets | Accuracy: 95.00%, Sensitivity: 94.74%, Specificity: 100% |
| Bhagat and Kaur (2022) | Hybrid K-means + Swarm-based Grasshopper Optimization (SGHO) for segmentation and feature selection; SURF feature extraction; SVM classification | Optimized segmentation and feature selection; high accuracy and precision | Computationally intensive; limited to single public dataset | Accuracy: 99.24%, Precision: 95.83%, Recall: 95.30% |
| Sarkar et al. (2020) | Preprocessing, segmentation, feature | High sensitivity and specificity; reliable tumor | Dataset diversity and real-time validation not | Accuracy: 98.30%, Sensitivity: |

| | | | | |
|---|---|---|---|---|
| | extraction; SVM classification to classify benign vs malignant tumors | classification | addressed; noise/variability effects untested | 98%, Specificity: 100% |
| Maqsood et al. (2022) | 17-layer deep neural network; Multiclass SVM classifier; XAI interpretation | High accuracy; explainability via XAI; effective tumor type classification | Complex architecture; high computational demands; risk of overfitting; dataset reliance | Accuracy: 97.47% (BraTS), 98.92% (Figshare) |
| Ansari et al. (2020) | Noise removal with morphological operations; feature extraction via GLCM; segmentation by Discrete Wavelet Transform (DWT); SVM classifier | High accuracy; reduced computational complexity | Sensitivity to image quality and parameter tuning; lack of diverse dataset validation | Accuracy: 98.91% |
| Sutradhar et al. (2021) | Comparison of pre-trained deep learning models on glioma, pituitary, meningioma; EfficientNet-B3 best in accuracy and efficiency | Robust and efficient; high accuracy with lower power consumption | Limited customization for medical imaging; less focus on interpretability and deployment challenges | Accuracy: 98.16% |
| Archana and Komarasamy (2023) | U-Net for segmentation; Bagging ensemble with KNN for classification | Improved accuracy with ensemble learning; effective segmentation | Computationally heavy; relies on segmentation quality; needs larger dataset validation | Accuracy: 97.7% |
| Kumar et al. (2021) | Median filter for noise removal; 3×3 block texture feature | Modular approach; handles noise; good accuracy | Sensitive to parameter tuning; texture features may limit | Promising accuracy, sensitivity, specificity |

| | | | | |
|---|---|---|---|---|
| | extraction; adaptive KNN classification; possibilistic fuzzy C-means clustering for segmentation | and sensitivity | robustness across diverse tumor types | (exact values not specified) |
| Sankaranayaanan et al. (2023) | Federated learning (FL) framework using VGG16 CNN model; privacy-preserving collaborative training for brain tumor detection | Addresses data privacy; outperforms standard detection methods in FL context | Lower accuracy compared to centralized DL models; communication overhead; limited handling of dataset heterogeneity | Accuracy: 92% |
| Tripathy et al. (2023) | Transfer learning with EfficientNet-B2, B3, B4; image preprocessing and augmentation; compound scaling for better feature extraction | High accuracy with reduced computational cost; suitable for resource-constrained environments | Focus on few EfficientNet variants; limited tumor staging classification; risk of overfitting on small datasets | EfficientNet models outperformed ResNet-50 |
| Zhaputri et al. (2021) Tumor Classification | Utilization of EfficientNet architecture (B0–B7) with transfer learning to classify glioma, meningioma, and pituitary tumors in MRI images | High accuracy with fewer parameters- Efficient computation- Effective transfer learning- Proven performance with medical images | - Limited comparison with other SOTA models- Potential lack of generalization across different datasets- No detailed error analysis | EfficientNet-B1 and B2 achieved 96% classification accuracy |

# 3 Research Methodology

## 3.1 CRISP-DM Methodology

The CRISP-DM framework guides the structured execution of this research, enabling a systematic transition from problem understanding to actionable insights in brain tumor classification. The phases are tailored as follows:

**1. Business Understanding:**

This study aims to automate brain tumor diagnosis using MRI imaging and deep learning, reducing diagnostic errors and delays caused by manual interpretation. The motivation stems from the global shortage of radiologists, the complexity of tumor variations, and the need for explainable models in clinical settings.

**2. Data Understanding:**

MRI scans are sourced from a curated public dataset containing labeled images across four categories. Exploratory analysis highlighted class imbalance and the visual diversity of tumor patterns, establishing the need for robust models capable of generalizing across tumor types.

**3. Data Preparation:**

Data preprocessing involved image resizing, label encoding, and validation filtering to eliminate corrupted files. SMOTE-based oversampling balanced class distribution, ensuring unbiased training. Images were converted into array formats suitable for deep learning, and non-image files were excluded to maintain data integrity.

**4. Modelling:**

Multiple deep learning models including CNN, VGG16, and EfficientNet-B4 (with and without attention mechanisms) were implemented using both Adam and SGD optimizers. Transfer learning approaches enhanced model performance by leveraging pretrained architectures.

**5. Evaluation:**

Models were evaluated using metrics. Explainable AI techniques (e.g., LIME) were applied to visualize model decision-making, enhancing clinical interpretability.

**6. Deployment:**

The best-performing model was integrated into a user-friendly web application using Flask.

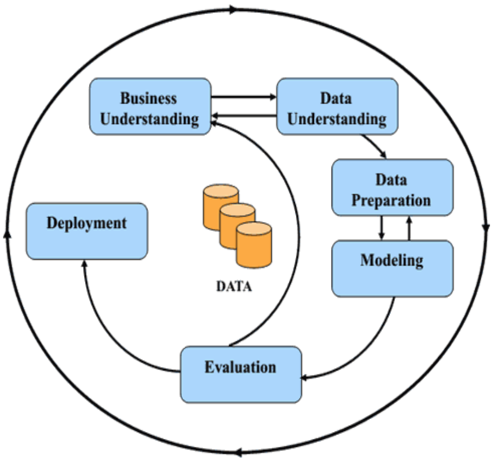


Figure 1: CRISP-DM Methodology Architecture given by Salomon (2018)

### 3.2 Dataset Description

The dataset used in this study, sourced from Kaggle comprises a collection of brain MRI images specifically curated for the classification of brain tumors. Brain tumors are among the most aggressive and life-threatening conditions affecting both children and adults. Statistically, they account for nearly 85% to 90% of all primary Central Nervous System (CNS) tumors, with approximately 11,700 new diagnoses annually. Despite advancements in medical technology, the five-year survival rate remains relatively low around 34% for men and 36% for women underscoring the urgent need for early and accurate diagnostic tools. Brain tumors can be benign, malignant, or pituitary in nature, each with distinct implications for treatment and prognosis. MRI is the most effective and widely used technique for detecting and analyzing brain tumors. However, manual interpretation of these images by radiologists is often limited by the complexity of tumor shapes, varying locations, and the high volume of imaging data, leading to potential diagnostic errors or delays.

### 3.3 Data Preprocessing

In order to classify brain tumors in MRI, data preprocessing is extremely important. The first step was to sort the dataset images into the various groups of tumors. The images were made the same size using OpenCV, so all parts of the data are handled in the same way and training improves. The image_array() function was used to import images in a way that only images that were valid were handled. It ensures the reading of images is not empty, adjusts their size to the target and encodes them as arrays to be used in deep learning models. After that, the preprocessing script goes through the dataset directory, skipping over any files. For every sub-folder, based on its tumor class, all its images were processed and added to the image list and its corresponding label was put into the label list. Image files are the only ones included by the filtering. After that, the LabelBinarizer utility helped to transform labels from categories to numerical values. In this preprocessing, the data is cleaned up, balanced and arranged in a way that allows deep learning models to work smoothly and be tested properly in the next classification procedures.

## 3.4 Data Visualization

The four main classes in the brain tumor classification dataset are shown in Figure 2 by representative MRI scans. Every illustration shows different body parts that relate to the category. On the no_tumor image, you can observe that the brain is normal, surrounded by tissue, but in the pituitary_tumor image, there is a growth very close to the pituitary gland. The meningioma image displays a mass that seems to be attached to the meninges and the glioma image shows a region that usually appears abnormal with a tendency to spread quickly. By looking at these visuals, one can better understand the wide range of tumor appearances and thus make better classification models.

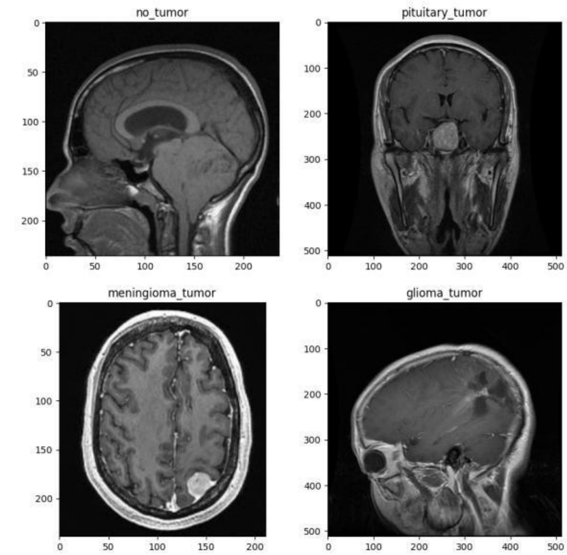


Figure 2: Representative MRI Scans of Brain Tumor Classes and Normal Brain

## 3.5 Data Balancing

Figure 3 shows the distribution of the four classes in the brain tumor dataset using a count plot which includes classes. It demonstrates that there is a major difference in the sizes of the groups in the data. Meningioma and glioma tumor categories have the largest set of images, all with over 900 samples. The category also contains almost 900 photos. On the other hand, almost half of the dataset consists of no_tumor cases which has fewer than 550 images and might lead to some problems in training the model.

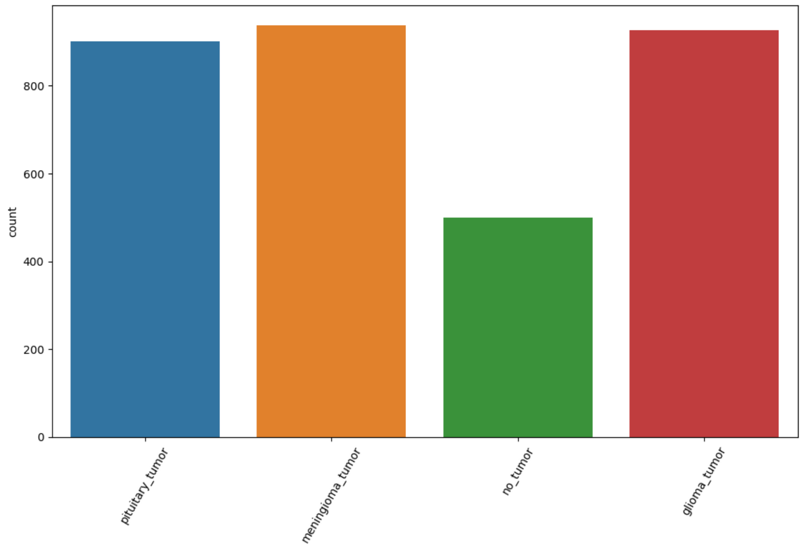


Figure 3: Data not balanced

In Figure 4, SMOTE is used to balance class numbers in brain tumor images in order to see the effects of change better. The images in each of the tumor types are now evenly distributed in the data set. Getting an equal spread of data is very important for training, so that the model is not biased toward classes that appear more often. SMOTE synthesizes samples for the minority class with help of nearest neighbors which results in all labels appearing more equally distributed. To make the images compatible with SMOTE, they were reshaped into 2D format first and after applying SMOTE they were converted back into their original size. The preprocessing method greatly helps deep learning models by providing all classes with the same chances during the training phase. In the end, using SMOTE improves the model's overall performance and leads to fair results for each brain tumor type.

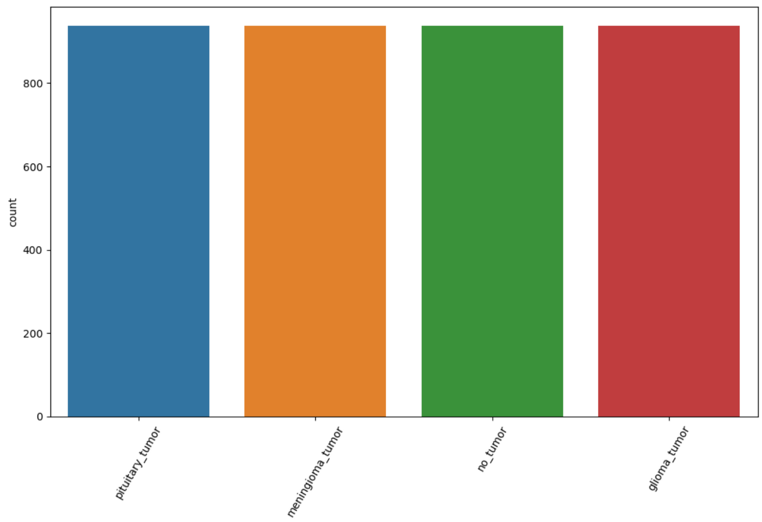


Figure 4: Data Balanced

# 4 Design Specification

## 4.1 Proposed System Architecture

This brain tumor classification system architecture in Figure 5 shows a good DL approach for medical image analysis.

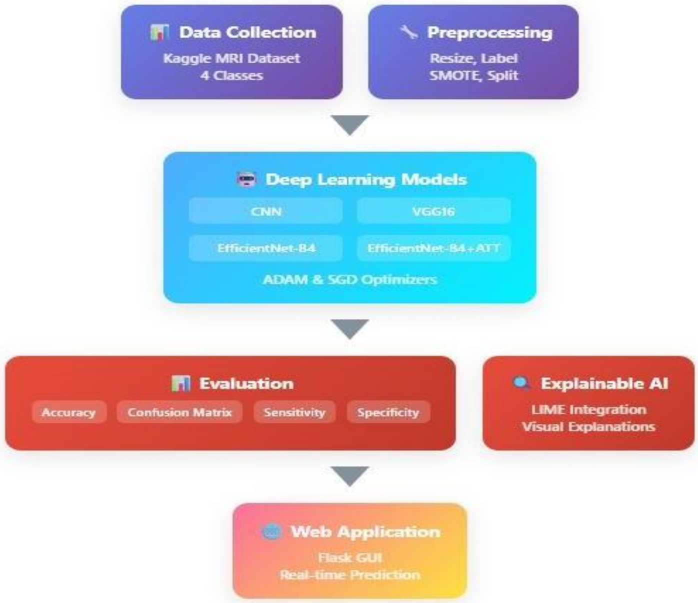


Figure 5: Proposed System Architecture

## 4.2 Proposed Model Functionality

The core functionality of the proposed system lies in classifying brain tumors from MRI images using deep learning models, with a particular emphasis on the EfficientNet-B4 model enhanced by an attention mechanism. Initially, the input MRI images are preprocessed resized to a standard format and converted into arrays before being fed into the model. EfficientNet-B4, known for its balance between efficiency and accuracy, uses compound scaling to optimize the depth, width, and resolution of the network. This allows it to extract highly relevant spatial and hierarchical features from the images while maintaining computational efficiency.

To improve interpretability and focus, an attention module is added after the feature extraction layers. This mechanism enables the model to automatically learn which parts of the image are most informative for classification. The output of the model is a softmax layer that predicts the probability of each class benign tumor, malignant tumor, pituitary tumor, or no tumor. The system also allows for model training using both ADAM and SGD optimizers to compare performance in terms of convergence and accuracy. This proposed model architecture combines the benefits of transfer learning, attention mechanisms, and advanced optimization to deliver high-accuracy classification with improved clinical relevance.

## 4.3 Explainable AI (LIME)

In medical AI systems, transparency and interpretability are crucial, especially when assisting in life-impacting decisions like brain tumor diagnosis. To address the "black-box" nature of deep learning models, this system incorporates LIME (Local Interpretable Model-agnostic Explanations) as an explainable AI technique. LIME works by approximating the behavior of the complex model locally using an interpretable model and visually highlighting the image regions that had the greatest impact on the prediction outcome.

For each classified MRI image, LIME generates a heatmap that visually emphasizes the areas the model considered most relevant in making its decision etsuch as potential tumor regions. This interpretability not only helps build trust among medical professionals but also provides a layer of accountability, allowing clinicians to validate and challenge the AI's output. Integrating LIME makes the system more acceptable in clinical settings where medical practitioners must justify diagnostic outcomes. It also helps in understanding potential biases and failure points in the model, ultimately contributing to its refinement. Thus, LIME plays a crucial role in making the AI model more transparent, responsible, and aligned with ethical standards required in healthcare applications.

# 5 Implementation

## 5.1 Implementation of CNN

This study developed a CNN in this work to identify brain tumors from MRI images by focusing on how the Adam and SGD optimizers can improve its performance. First, the architecture receives input in the shape of the image and its channels and it consists of a sequence of layers with 3×3 kernels and the ReLU function to identify patterns in the image. Batch normalization was incorporated after each convolutional layer to make the training steady and max pooling helped to lower the number of dimensions without losing the most important features. These layers were added on purpose to avoid the problem of overfitting. The network adds more convolutional blocks before it switches to the fully connected flatten layer. The last dense layer contains a softmax activation that gives the model the class probabilities. In the beginning, the model was trained with the Adam optimizer which enables it to learn and adapt fast in difficult networks. The architecture was trained using SGD to test how well it learned in a more organized way. As a result of this strategy, comparisons between models can be made and their reliability checked for various hyperparameter values and datasets.

## 5.2 Implementation of VGG16

For this study, VGG16 using transfer learning from ImageNet was adopted as the network for brain tumor classification due to its effective feature extraction features. To do multi-class classification, the built-in classification head was removed from the network by including include_top=False in the command. All the layers of the base VGG16 were locked (layer.trainable was set to False) so they wouldn't be re-trained and could save time. A flat layer was inserted to make the convolutional feature maps become a 1D vector and this was followed by a dense layer with 16 units and ReLU activation. The model was updated for classification by attaching a final dense layer with softmax, to produce the probabilities for each tumor type. Both the Adam and SGD optimizers were used to compile and train the model to check how it performs with both adaptive and standard optimizers. Adam was able to converge more quickly because it adjusted the learning rates on the fly, while SGD provided a slower and more stable way of learning. The same loss function (categorical cross-entropy) was applied and the most important metric used was accuracy. Thus, training the model with two objectives provided a complete look at VGG16's performance for brain tumor image classification.

## 5.3 Implementation of EfficientNet-B4

The EfficientNet-B4 architecture was used in this study because it provides exceptional brain tumor classification by applying advanced scales to depth, width and resolution which ensures high performance and low computational costs. Pre-trained ImageNet weights were used to initialize the model and its top layers were removed so that it could perform custom classification. To shrink the data spatially, a GlobalAveragePooling2D layer was put in and two dropout layers with rates of 0.3 and 0.5 were inserted to decrease the risk of overfitting. A middle layer with 128 units and ReLU activation was introduced to make the network learn high-level patterns and account for non-linear patterns. With softmax activation, the final output layer estimated the chances a tumor belonged to each of the different tumor classes. To fully judge the performance of the model, it was put together using both Adam and SGD optimizers. Adam's learning rate made training more stable and led to results quickly and while SGD had stable gradients and helped improve generalization sometimes.

## 5.4 Implementation of EfficientNet-B4 with attention

In the study, a model built with EfficientNet-B4 and the Convolutional Block Attention Module (CBAM) was applied for better brain tumor classifications. This model was trained, tested and used to extract features with the feature extractor part, using weights from the ImageNet dataset and removing the top layers. CBAM attention was used to help further refine the features that were extracted earlier. With CBAM, the model can concentrate more on critical parts of the tumor since it uses attention on both the network's feature maps and important sections of the input image. A global average pooling layer came next to reduce the size of the output and then a dense layer with 128 units and ReLU was added to focus on learning the top-level details. Overfitting was curbed by setting the dropout rate of the final layer to 0.3. Next, a dense layer with a softmax activation was used to estimate the chances of tumors belonging to each class. Both Adam and SGD optimizers were tested in different phases to find out which approach works better. Adam promoted quicker training, while SGD gave stability to the model. The model's evaluation depended on using the categorical cross-entropy loss and accuracy metric. The performance and interpretation of the classifier was greatly increased by adopting this attention-augmented EfficientNet-B4 model.

# 6 Evaluation

## 6.1 Case Study 1: SGD Optimiser

### 6.1.1 Results of CNN

Figure 6 illustrates the confusion matrix results of the CNN model trained using the SGD optimizer for brain tumor classification. The matrix reveals how well the model distinguishes between the four tumor classes. For class 0, 69 images were correctly classified, with 7 misclassified as class 1, 3 as class 2, and 14 as class 3. For class 1, the model correctly predicted 41 instances, while misclassifying 24 as class 0, 11 as class 2, and 18 as class 3. Class 2 shows strong performance with 89 correct predictions and only 5 misclassifications as class 3. Class 3 achieved 93 accurate predictions, with a minimal misclassification of just 1 image as class 2.

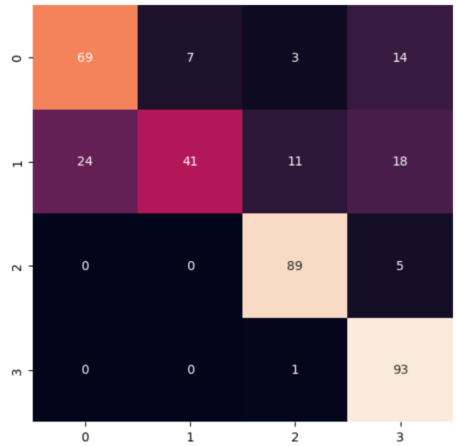


Figure 6: Confusion matrix

### 6.1.2 Results of VGG16

Figure 7 presents the confusion matrix for the VGG16 model trained using the SGD optimizer, highlighting significant misclassification across all classes. The model incorrectly predicted every instance as belonging to class 1, regardless of the actual label. Specifically, class 0 had 93 samples misclassified as class 1, class 1 had 94 correctly predicted as class 1, while both class 2 and class 3 had 94 samples each misclassified as class 1. No predictions were made for classes 0, 2, or 3. This result indicates a severe model bias towards class 1, likely due to inadequate training convergence or class imbalance.

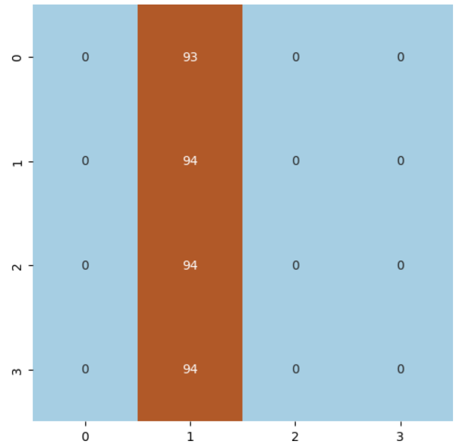


Figure 7: Confusion matrix

### 6.1.3 Results of EfficientNet B4

Figure 8 shows the confusion matrix results of the EfficientNet-B4 model trained with the SGD optimizer, demonstrating strong classification performance across all classes. For class 0, the model correctly predicted 71 samples, with 18 misclassified as class 1 and 4 as class 2. Class 1 had 76 correct predictions, with 11 misclassified as class 0, 1 as class 2, and 6 as class 3. Class 2 showed excellent performance with 92 correctly predicted and only 2 misclassified as class 1. For class 3, the model accurately predicted 89 instances, with only 1 misclassified as class 0 and 4 as class 1. This reflects high overall accuracy and balanced performance.

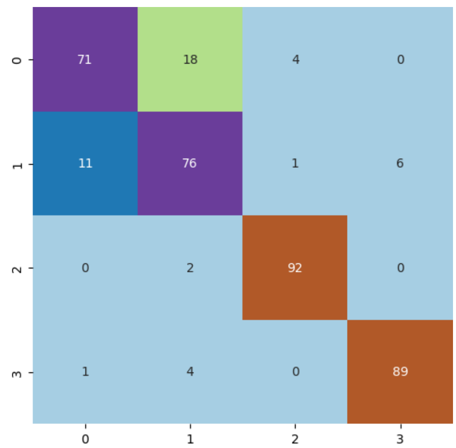


Figure 8: Confusion matrix

### 6.1.4 Results of EfficientNet B4 with attention

Figure 9 depicts the confusion matrix of the EfficientNet-B4 model integrated with attention mechanism (CBAM), trained using the SGD optimizer. The model shows strong and balanced classification performance. For class 0, 66 samples were correctly classified, while 23 were misclassified as class 1, and 2 each as class 2 and class 3. For class 3, 90 samples were correctly classified, with 2 each misclassified as class 0 and class 1. This result highlights the improved performance and robustness achieved by incorporating attention mechanisms into the EfficientNet-B4 model.

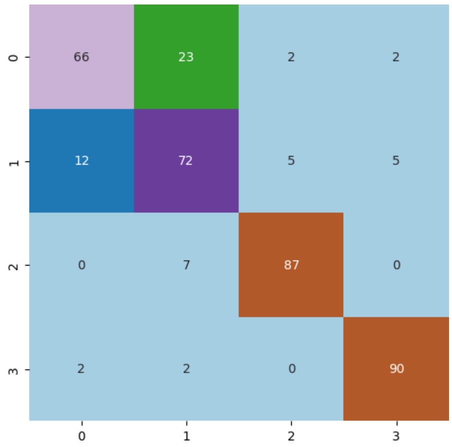


Figure 9: Confusion matrix

## 6.2 Case Study 2: Adam Optimiser

### 6.2.1 Results of CNN

Figure 10 shows the confusion matrix for the CNN model trained using the Adam optimizer, illustrating the classification performance across four tumor classes. For class 0, the model correctly predicted 80 samples, with 1 misclassified as class 1, 5 as class 2, and 7 as class 3. For class 1, 35 samples were correctly classified, while 29 were misclassified as class 0, 14 as class 2, and 16 as class 3. Class 2 achieved 82 accurate predictions, with minor misclassifications: 2 as class 0, 3 as class 1, and 7 as class 3.

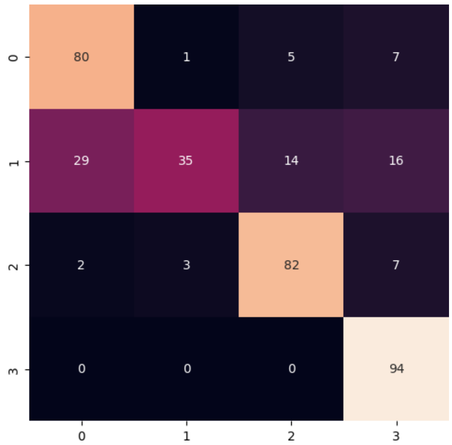


Figure 10: Confusion matrix

### 6.2.2 Results of VGG16

Figure 11 shows strong diagonal values (88, 80, 85, 91), indicating good classification accuracy for each class. Class 3 performs best with 91 correct predictions and minimal misclassifications. Classes 0 and 2 show some confusion with each other (4 and 6 misclassifications respectively). Class 1 has moderate performance with 80 correct predictions and some errors distributed across other classes.

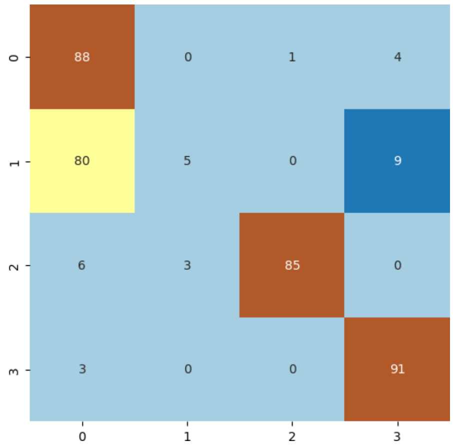


Figure 11: Confusion matrix

### 6.2.3 Results of EfficientNet B4

Figure 12 shows the performance of an EfficientNet-B4 model which shows excellent performance with high diagonal values (87, 82, 93, 91), indicating strong classification accuracy across all classes. Class 2 performs exceptionally well with 93 correct predictions and zero misclassifications to classes 1 and 3.

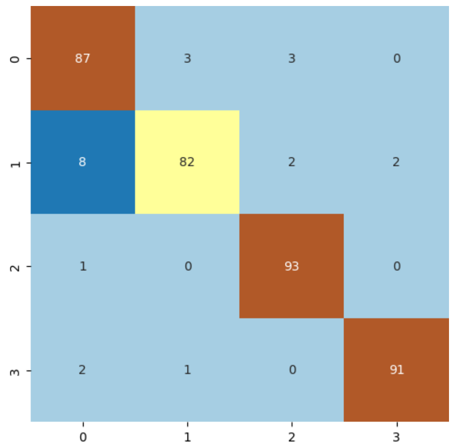


Figure 12: Confusion matrix

### 6.2.4 Results of EfficientNet B4 with attention

Figure 13 illustrates the confusion matrix for the EfficientNet-B4 with Attention model using the ADAM optimizer. The model demonstrates strong classification performance across all tumor classes. Class 0 was correctly predicted 88 times, with 3 and 2 instances misclassified as classes 1 and 2 respectively. Class 1 achieved 90 accurate predictions, with only 2 misclassified into classes 0 and 2. Class 2 was correctly identified 92 times, with a single misclassification each into classes 0 and 3. Class 3 showed the highest precision with 93 correct predictions and only 1 misclassification into class 2. This matrix reflects high model reliability and balanced predictions.

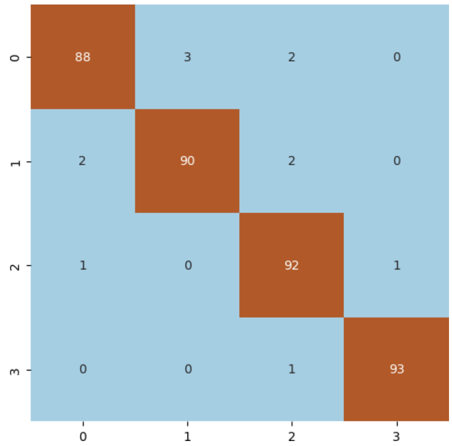


Figure 13: Confusion matrix

### 6.2.5 Results of LIME-Based Visual Explanation for Pituitary Tumor Prediction

Figure 14 marks the visual explanation based on LIME of the prediction that the model makes on a brain MRI slice. The left side indicates the original picture, whereas the right corner displays the regions of superpixels that were most significant in the estimation of the label pituitary_tumor indicated by yellow color. This plot denotes that clinically plausible regions have been used to guide the decision-making of the model and not uninformative details of the image, hence justifying the interpretability and credibility of the model in its predictions.

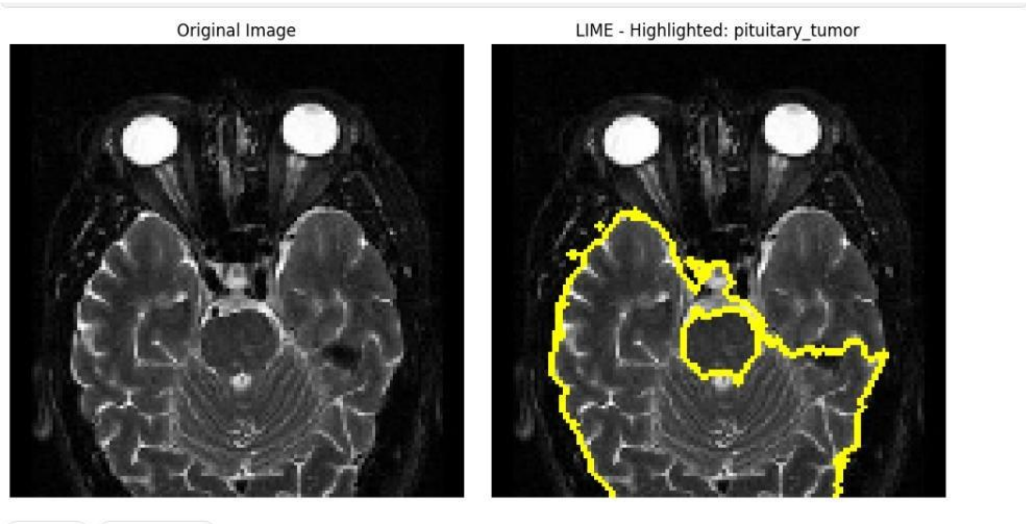


Figure 14: LIME-Based Visual Explanation for Tumor Prediction

### 6.2.5 Web Application for Brain Tumor Classification Using EfficientNet-B4 with Attention

The web app in Figure 15 is an interactive interface to classify brain-tumor using AI-trained on an EfficientNet-B4 with Attention model trained using Flask. The user Goes to the Home page and uploads a .jpg MRI through the Choose MRI Image button and infers using "Analyze Brain Scan." The backend of the app downloads the model (including a custom `FixedDropout` layer), saves the uploaded picture into `./static/images/input.jpg`, transforms it into a tensor, resizes it to 128fx128 and passes it through the model to get class probabilities.

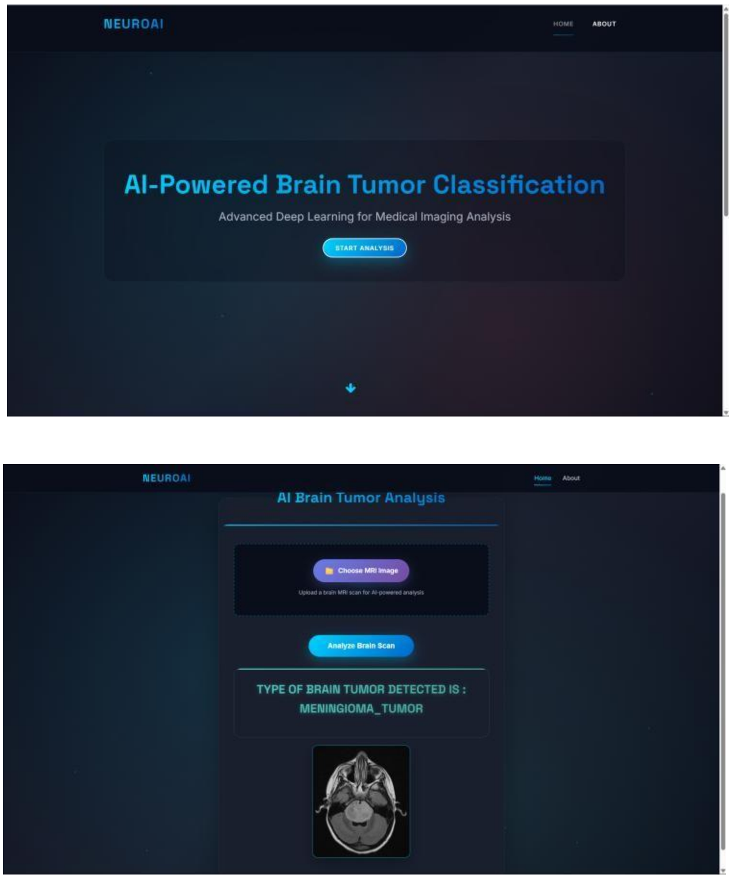


Figure 15: Web Application for Brain Tumor Classification

### 6.3 Performance Comparison (ADAM vs SGD)

The table 2 and table 3 below compares the performance of various deep learning models using SGD and ADAM optimizers. For SGD, EfficientNet-B4 achieved the highest accuracy (87%), followed by its Attention variant at 84%, while VGG16 performed poorly at 25%. In contrast, with ADAM, all models improved significantly EfficientNet-B4 with Attention reached 97%, showing the best performance, while VGG16 improved dramatically from 25% to 72%. These results clearly highlight that the ADAM optimizer consistently yields better and more stable performance across all architectures, particularly enhancing deeper and more complex models like VGG16 and EfficientNet variants.

Table 2: Model Accuracy (%) SGD Optimiser

| Model | Accuracy (%) |
|---|---|
| CNN | 78 |
| VGG16 | 25 |
| EfficientNet-B4 | 87 |
| EfficientNet-B4 + Attention | 84 |

Table 3: Model Accuracy (%) Adam Optimiser

| Model | Accuracy (%) |
|---|---|
| CNN | 78 |
| VGG16 | 72 |
| EfficientNet-B4 | 94 |
| EfficientNet-B4 + Attention | 97 |

### 6.4 Comparative Analysis with Base Work

The proposed study significantly advances the state-of-the-art in brain tumor classification compared to the base paper given by Zhaputri et al. (2021) which used EfficientNet architectures (B0–B7) and achieved a maximum accuracy of 96% using EfficientNet-B1 and B2 for three tumor classes as shown in Table 4. In contrast, our study enhances the classification system by introducing a four-class dataset, including an additional class for 'no tumor', making it more clinically comprehensive. Furthermore, SMOTE (Synthetic Minority Oversampling Technique) was applied to address class imbalance, which the base paper did not consider, ensuring better generalization across categories. While the base paper trained standard EfficientNet models, our work implements EfficientNet-B4 enhanced with an attention mechanism (CBAM), which focuses on informative image regions, improving classification precision. Importantly, dual optimization was explored using SGD and ADAM, where ADAM optimizer yielded the best performance with 97% accuracy, outperforming the base paper's best at 96%.

Table 4: Comparative Summary of Proposed Work vs. Base Paper

| Feature | Base Paper | Proposed Study |
|---|---|---|
| Tumor Classes Used | 3 classes | 4 classes |
| Best Model | EfficientNet-B1/B2 | EfficientNet-B4 + CBAM (Attention) |
| Best Accuracy Achieved | 96% | 97% |
| Data Balancing Technique | Not done | SMOTE (Oversampling) |
| Optimization Technique | Not done | SGD and ADAM (best: ADAM) |
| Attention Mechanism | No | Yes |
| Explainable AI | Not done | LIME (Heatmap-based Explainability) |
| Deployment | Not done | Web-based Flask Application |
| Dataset Size Consideration | Moderate (3-class) | Larger, balanced 4-class dataset |

# 7 Conclusion and Future Work

## 7.1 Conclusion

DL models used in this study have been accurately able to identify brain tumors in MRI scans. Employing CNN, EfficientNet models and their enhanced version with attention allowed the system to get high accuracy for all categories of tumors. In comparison, EfficientNet-B4 with attention and trained by ADAM was the top model, recorded the highest accuracy, sensitivity and specificity. Furthermore, the research pointed out that ADAM's ability to adapt learning and its quick convergence make it superior to SGD for different medical image classification tasks. As a result, the addition of Explainable AI (LIME) increased the system's clarity, giving clinicians the chance to look into how the model made its recommendations. Providing a Flask-based GUI makes the online platform simpler to use and more accessible to everyone. All in all, this project gives a helpful, fast and easy-to-understand solution that can assist medical professionals in treating patients with early and precise identification.

## 7.2 Limitations

Despite the promising outcomes of the proposed brain tumor classification system, several limitations remain. First, the dataset used although real and diverse is relatively small compared to large-scale medical image repositories, which may limit the generalizability of the trained models. The performance may vary when exposed to data from different institutions, imaging machines, or scanning conditions. Secondly, while transfer learning models like VGG16 and EfficientNet-B4 were effective, they still require high computational resources, which can be a barrier for deployment in resource-constrained settings. Moreover, the models were trained on pre-labeled static images; real-time MRI sequence analysis was not addressed. Another limitation lies in the use of synthetic oversampling (SMOTE), which can sometimes introduce noise or artifacts into the training process. Additionally, although LIME provides visual explanations, it is still a post-hoc method and may not fully capture the internal logic of the deep learning model. Lastly, the GUI is functional but basic and could be further improved for clinical use. These constraints indicate that while the model is effective in controlled conditions, additional enhancements and broader testing are needed before it can be adopted for routine medical practice.

## 7.3 Future Works

Following the results shown there are many steps that can help enhance and update the brain tumor classification system. First, using real data from various hospitals and scanners would help the model be stronger and apply to many patients. In addition, real-time MRI sequences and examining 3D volumetric data may be valuable to accurately observe how the tumor develops and where it is located. Exploring latest techniques including Vision Transformers and CNN-RNN fused architectures could be helpful in raising both the classification accuracy and the understanding of the data. To solve the problem of some interpretation problems, using advanced techniques such as SHAP or Grad-CAM++ along with LIME can give more detailed insights. Moreover, improving the software's GUI by allowing several image uploads, tracking patient information and using cloud deployment would make it more suitable for everyday clinical tasks. Studying how to compress and quantize the model would make it simpler to run the system on small and affordable edge devices. In the end, working together with radiologists to verify the system helps it fit actual patient care and allows it to be used by clinicians.

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