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Review Article

Brain Tumor Detection through Deep Learning-Based Medical Image Classification

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Abstract *- Magnetic Resonance Imaging (MRI) classification of brain tumors has become a needed procedure in clinical diagnosis, where correct and timely diagnosis could be very useful in the planning of treatment and the outcome of the patient. Nevertheless, current methods of deep learning are largely limited to generalization because of single -dataset dependence, absence of attention, and interpretability. In response to these issues, this paper suggests a multi-faceted deep learning-based model of robust brain tumor classification with the use of heterogeneous MRI data. The main purpose of the study is to construct and test the effective classification model with multiple convolutional neural (CNN) architectures and attention-increased models. To guarantee the cross-dataset validation and strength, the study utilizes two publicly available datasets- the Figshare Brain Tumor Dataset and BraTS2020. All MRI images are subjected to a standardized preprocessing pipeline that includes resizing, normalization, and data augmentation. CNN-based VGG16, ResNet50, AlexNet, EfficientNetB0, and a newly designed lightweight LeNet with Squeeze-and-Excitation (SE) blocks are trained and optimized through transfer learning and tuned hyperparameters. Further, the experimental results will show that the suggested LeNet + SE model has the highest performance on the BraTS2020 dataset, having an accuracy of 98.44, precision of 98.43, recall of 98.44, and F1-score of 98.43. VGG16 and ResNet50 have the highest accuracy of 93.31 on the Figshare dataset, which means that they have good classification by structured MRI data. The high accuracy of the suggested model makes the focus of attention-based channel recalibration efficient in capturing discriminative tumor features without a significant sacrifice in computational efficiency. The proposed framework has great potential in improving the robustness, generalization, and interpretability of brain tumor classification that can be utilized as a reliable method of classifying medical images.*

Keywords *- Brain Tumor, Deep Learning, Medical Imaging, Image Classification, Tumor Detection*.

1. Introduction

Among the most serious and fatal diseases in medicine, brain tumors require correct diagnosis right away to be treated successfully. Early identification lowers possible neurological damage and enables quick action, hence improving patient outcomes. especially Magnetic Resonance Imaging (MRI), the diagnosis of brain tumors has depended on the hand interpretation of medical imaging. Although efficient, these traditional approaches rely on the radiologist's expertise and skill, are time-intensive, and prone to human error. Deep learning has become a potent weapon for increasing diagnosis accuracy and efficiency by means of automated medical picture classification in recent years. A subset of Artificial Intelligence (AI), deep learning processes complicated datasets and generates data-driven conclusions using Artificial Neural Networks [1-3]. Through automatically learning hierarchical features from raw picture data, Convolutional Neural Networks (CNNs) in particular have transformed image analysis. CNNs can effectively differentiate between tumor-affected areas and healthy tissues applied to brain MRI imaging. They can even identify minor anomalies that could be missed by human viewers [4-7]. Deep learning is particularly useful in radiology, where accuracy and speed are critical, because of these features. Deep learning in brain tumor identification has been motivated by developments in processing capability and the availability of huge, annotated MRI datasets. These models give thorough localization and segmentation in addition to tumor presence identification, thereby illuminating tumor kind, size, and precise position. Directly affecting patient care and prognosis, surgery planning and treatment strategies rely on such thorough knowledge [8-11]. Models useful in a variety of clinical environments can generalize across different patient demographics and imaging equipment, so they are trained on several datasets. Deep learning's consistency is among its most important advantages for diagnosis [12-14]. Deep learning models are capable of delivering reproducible outputs regardless of external factors, compared to traditional processing, which may have inter-observer error or poor quality imaging. Their unusual speed in analyzing hundreds of photos in a few seconds, in highdemand clinical or emergency scenarios, is critical, in particular, as their functionality improves over time in relation to new imaging modalities and clinical requirements. Even when it comes with several advantages, deep learning-based brain tumor identification has a number of challenges. The quality and quantity of training data are critical to the extent to which these models can be effective. The difference in the technique of MRI, scanner models, and the diversity of the population may introduce prejudices affecting the accuracy of the model [15-20].

Moreover, the black-box or opaque nature of most deep learning algorithms raises the question of interpretability and confidence in therapeutic practice. Scientists are developing explainable artificial intelligence systems, which offer visual or text figures to explain the conclusions of the model to address the issue and hence increase clinician confidence and disclosure. Through automated, precise, and quick analysis of medical images, deep learning is a disruptive approach to brain tumor diagnosis. These systems can revolutionize the process of diagnosis, decrease the number of human errors, and offer personalized healthcare due to constant improvements in neural networks, data access, and collaborative studies. A key to successful integration of deep learning into real-life clinical practice is continuous effort in validation, ethical development, and interdisciplinary collaboration [21, 22].

1.1. Background and Contextual Framework

1.1.1. Historical Overview and Evolution of the Topic

There has been an impressive change in recent years from manually examining radiological images to highly automated systems that are AI-driven in detecting the presence of a brain tumor. The MRI and CT scan interpretation is an imperfect and subjective process for radiologists to make most of the diagnoses. The first application of standard Machine Learning (ML) methods involving feature addition, manually, in order to classify medical images, can be found in the late 20th century, with the emergence of computing power. These methods did not support both scalability and information generalization [23-26]. Convolutional Neural Networks (CNNs) represent a branch of deep learning and have achieved a lot of success in the early twentieth century; the networks are good at identifying meaningful patterns in large datasets in healthcare. Datasets with annotations became more available, and models such as ResNet, AlexNet, VGG, and other domain-specific architectures were changed accordingly to address the challenges of brain cancer classification. Such models are more accurate, sensitive, and robust compared to the ML approaches. Recent developments have combined explainable AI, transfer learning, and hybrid models to enhance clinical reliability and interpretability. The fact that deep learning is capable of delivering accurate, faster, and scalable solutions is a sign of a larger trend within the medical diagnostics field toward the direction of better patient outcomes in neuro-oncology by means of earlier diagnosis, more accurate treatment planning, and reduced treatment time.

1.1.2. Relevance to Current Research Landscape

Deep learning-based brain tumor detection is a very topical topic of research in the modern environment of the world of medicine, in which the most important aspects are accuracy and efficiency in medical diagnosis. As the occurrence rates of brain tumors have been on the rise, early and precise diagnosis is the only way to treat them successfully. The use of deep learning models, and specifically the Convolutional Neural Networks (CNNs), has demonstrated better results in predicting brain tumors on MRI images when compared to conventional techniques. The development is part of a larger trend of applying artificial intelligence to the healthcare industry to improve the accuracy of diagnosis and decrease the amount of work of clinicians [27-30]. Access to big annotated datasets and better computational capabilities have boosted the creation of powerful and scalable models. The current state of research is related to solving such critical issues as model interpretability, real-time functioning, and its ability to generalize to various populations. In addition, medical imaging and personalized medicine, as well as decision support systems in the field of neuro-oncology, are highly impactful and progressive due to the contribution of these innovations, which are not only advancing the field but also playing a significant role in it.

1.2. Research Gap and Novelty

The existing efforts by researchers in brain tumor classification have been predominantly founded on single data sets, deep learning networks with great computational demands, and uneven experimental results, and cannot be used to extend the models to clinical settings. Moreover, it is not focused on explainability, reducing the trust in automated diagnostic systems. In order to address such gaps, the current paper introduces a new cross-dataset deep learning system that compares different CNN structures at preprocessing and hyperparameter conditions in a systematic manner. Its remarkable innovation is that Squeeze-and-Excitation (SE) attention has been incorporated into a model with minimal computational cost, and that enhanced differentiation of features can be achieved at a low cost, and transparency and clinical significance are ensured with Grad-CAM and LIME.

This paper fills these gaps by introducing a single deep learning architecture that combines Squeeze-and-Excitation (SE) attention, multi-scale feature extraction, and 1x1 convolutional compression to four architectures: VGG-16, ResNet-50, AlexNet, and LeNet. Stratified splitting and a regular preprocessing pipeline guarantee the quality of inputs and reliability, respectively. It is found that the hybrid VGG-16 model is more efficient based on classification, denoting the relevance of architectural design and channel attention. The proposed solution can be added to the accuracy, strength, and practical use in automated brain tumor diagnosis.

2. Literature Review

Ahmed 2023 et al. Despite the fact that advances in artificial intelligence have greatly enhanced prediction and detection accuracy using non-invasive imaging technologies, brain disease diagnoses, especially brain tumors, face growing difficulties. Since brain tumors are still fatal, AI-assisted surgery provides better and safer treatment.

Still, major problems include limited annotated datasets, lack of interpretability, variation in tumor location, shape, and size, and challenges in external validation. While cancer knowledge limits integration, the black-box aspect of artificial intelligence further challenges clinician trust. Emerging directions include radionics, interpretable deep learning, and joint projects by professional bodies to remove challenges and improve the influence of artificial intelligence in healthcare [31].

Yousef 2023 et al. The radiologists' ongoing struggle with brain tumor segmentation from MRIs highlights the need for a standardized, automated approach. The use of U-Net-based models for medical image segmentation in many modalities is widespread. explores new U-Net topologies with the aim of enhancing the performance of brain tumor segmentation.

With an eye on optimization improvements, we provide an analysis of several U-Net variations. Experiments comprising four architectures-3D U-Net, Attention U-Net, R2 Attention U-Net, or modified 3D U-Net-evaluate performance via Dice score and Hausdorff distance 95% using the BraTS 2020 dataset. Explored are the constraints and restrictions, with an emphasis on the necessity of next-generation segmentation models that are optimal [32].

Martucci 2023 et al. For the diagnosis, plan of action, and monitoring of treatment response or recurrence of brain tumors, Magnetic Resonance Imaging (MRI) is fundamental. Modern neuroimaging techniques enhance diagnostic precision and follow-up by revealing morphologic and non-morphologic features, including metabolic, functional, cellular, and genetic factors.

To use sound clinical judgment and accurate interpretation, one must be familiar with the benefits and limitations of each MR technique. Employs conventional Magnetic Resonance Imaging (MRI) while systematically exploring cutting-edge non-morphological methods. Additionally, it delves into potential future paths, such as radionics and AI, highlighting their potential to revolutionize brain cancer evaluation and encourage more personalized treatment strategies in instances of primary brain tumors in adults [33].

Venmathi 2023 et al. Improving survival odds requires early diagnosis of a brain tumor. To improve the accuracy of diagnoses, this study utilized MRI-based analysis and implemented a hybrid enhanced Convolutional Neural Network with Deep Convolution (DCNN) that utilized the VGG-19 algorithm. Finding the precise site of the tumor and determining whether it was benign or malignant were the goals of the approach.

We used a Laplacian Logarithmic (LOG) filter to process the divided dataset. We used recall, specificity, accuracy, and precision to measure performance. By improving classification efficiency with deep learning approaches, the suggested model outperformed previous methods and attained an accuracy rate of over 99.65% [34].

Shawon 2023 et al. (2023) investigate the possibility of detecting brain tumors by means of automated classification and time reduction through the use of NASNetMobile, EfficientNetB0, InceptionV3, ResNet50, and CNN. After fine-tuning InceptionV3, an automated process using these models achieved 99.33% accuracy on a balanced dataset. We used explainable AI approaches to decipher the behavior of the models. After using a cost-sensitive neural network technique, CS-InceptionV3 achieved 92.31% accuracy, and CS-CNN achieved perfect recall in handling imbalanced datasets. These models show great promise for clinical application and considerably enhanced tumor detection accuracy. For those interested in delving deeper into the subject, the datasets and code are openly accessible [35].

Table 1. Literature Summary

Authors/year	Methodology	Research gap	Findings
Agarwal/2023 [36]	CNN, ResNet50, InceptionV3 EfficientNetB0, NASNetMobile.	Limited interpretability, imbalanced datasets, and inconsistent accuracy in tumor detection.	High accuracy, improved recall, effective on imbalanced data, and enhanced interpretability.
Bianchessi/2023 [37]	Deep learning, MRI, classification, fusion, and explainability.	Limited pediatric tumor classification, adult-trained models, low explainability, and data fusion are underexplored.	A shallow custom network with age fusion achieved the highest classification performance.
Gajre/2022 [38]	Transfer Learning, Classic Neural Networks,	Lack of unified analysis, limited model comparison, and unclear performance benchmarks.	Deep learning models show strong performance;

	Convolutional Neural Networks (CNN).		comparison reveals strengths, limitations.
Khekare/2022 [39]	Deep learning, preprocessing, MRI, detection, experimentation.	Existing techniques struggle with tumor variability in shape, size, and location.	Deep learning improves tumor detection accuracy across diverse MRI image datasets.
Nayak/2022 [40]	Preprocessing, deep learning, and MRI analysis.	Difficulty detecting tumors due to variability in shape, size, and location.	Deep learning enhances tumor detection accuracy despite diverse MRI challenges.

Though the previous works provide good results with convolutional neural networks and transfer learning in brain tumor classification, the current literature is disjointed and usually restricted to the data set analysis.

Most of these methods do not include cross-dataset validation, are based on varying experimental conditions, and offer weak benchmarking across a variety of CNN architectures. Besides this, model interpretability is often insufficiently investigated, which lowers clinical trust and transparency. Although accuracy has been highly considered, explainability and strength under heterogeneous imaging situations are not adequately addressed.

To fill these gaps, this research suggests an integrated and benchmarked deep neural network, which compares several CNN frameworks in the context of standardized preprocessing and hyperparameter conditions on two heterogeneous MRI datasets.

The use of a lightweight Squeeze-and-Excitation (SE)-enhanced LeNet architecture, along with explainable AI methods, including Grad-CAM and LIME, enables better discriminating features and interpretability, which is used to achieve better robustness, transparency, and clinical usefulness in automated brain tumor classification.

3. Research Methodology

This study presents a comprehensive and comparative deep learning–based framework for brain tumor classification using multi-source MRI data, with a strong emphasis on robustness, generalizability, and model interpretability.

Unlike prior studies that rely on a single dataset or a single model architecture, the proposed methodology integrates cross-dataset validation, architecture diversity, and attention-enhanced learning to address key limitations in existing brain tumor classification research.

A major novelty of this work lies in the simultaneous utilization of two heterogeneous public datasets-Figshare and BraTS2020, which differ significantly in image complexity, acquisition protocols, and clinical variability. While Figshare provides structured single-modality MRI images suitable for supervised classification, BraTS2020 introduces multi-institutional, multi-modal MRI data. Employing both datasets within a unified framework enables rigorous evaluation of cross-dataset generalization, a critical yet underexplored aspect in medical imaging studies. Another key contribution is the systematic comparison of classical, deep, lightweight, and attention-augmented CNN architectures, including VGG16, ResNet50, AlexNet, EfficientNetB0, and a novel LeNet enhanced with Squeeze-and-Excitation (SE) blocks.

The integration of SE modules into a shallow LeNet architecture represents a methodological advancement, as it enables channel-wise feature recalibration while maintaining low computational complexity. This design demonstrates that effective attention mechanisms can be embedded into lightweight networks to improve discriminative learning without relying solely on very deep architectures.

The study further contributes by adopting a standardized and empirically validated hyperparameter configuration across all models, addressing a common limitation of prior works that employ arbitrary or inconsistent training settings. By maintaining uniform preprocessing pipelines, optimization strategies, and evaluation protocols, the methodology ensures fair architectural comparison and reproducibility.

In addition, the framework incorporates explainable AI (XAI) techniques, specifically Grad-CAM and LIME, to enhance model transparency and clinical trustworthiness. These interpretability tools provide visual insights into the regions influencing classification decisions, bridging the gap between black-box deep learning models and clinical applicability.

Finally, the methodology conceptually extends toward privacy-preserving medical AI by proposing a federated learning paradigm for future implementation. This highlights the study’s forward-looking contribution to ethical and scalable deployment of deep learning models in real-world healthcare environments.

The proposed methodology advances the field of brain tumor classification by combining cross-dataset learning, attention-based lightweight modeling, standardized experimentation, and explainability, thereby offering a robust, interpretable, and generalizable framework for medical image analysis.

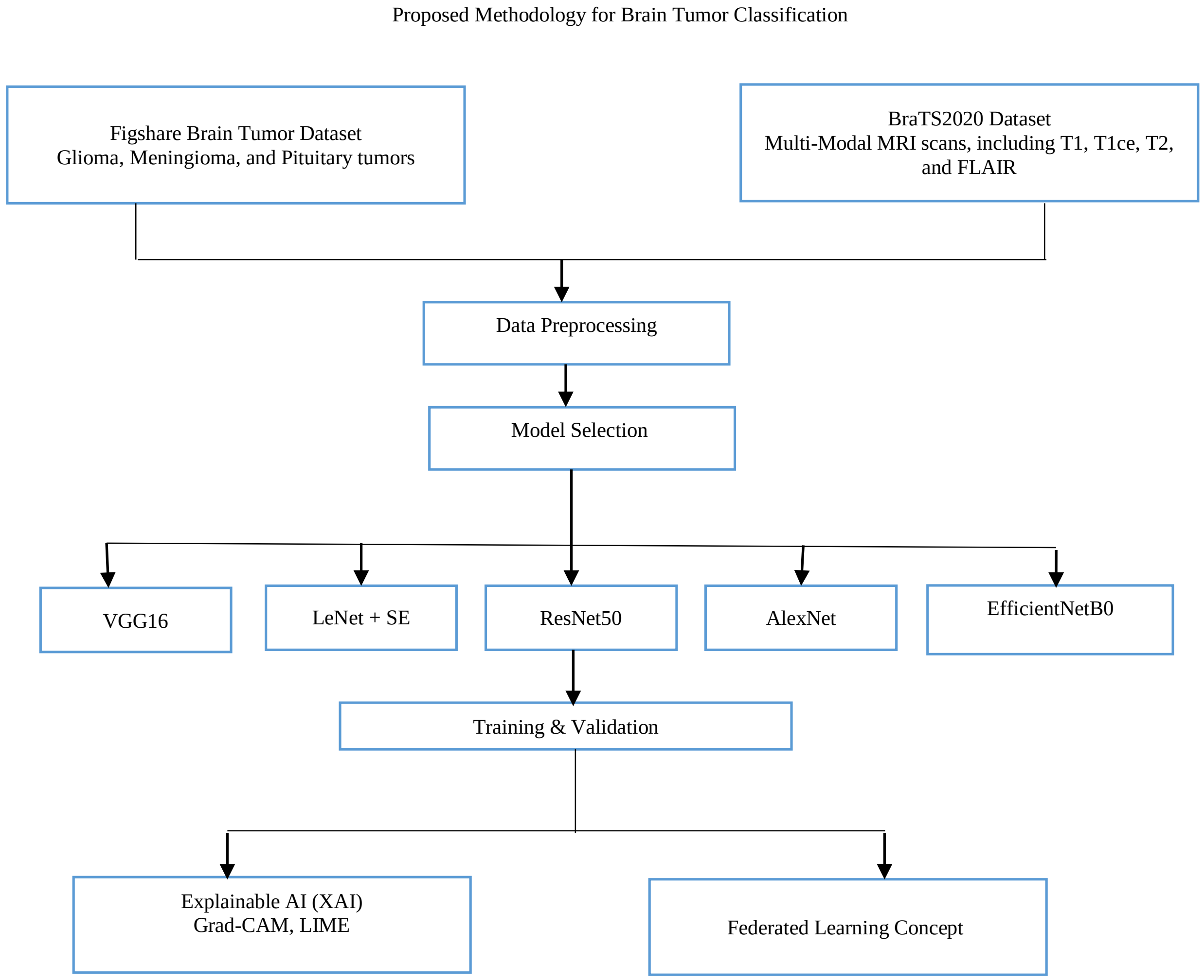

Fig. 1 Proposed Flow Chart

3.1. Data collection

The two publicly available, widely used brain tumor imaging datasets are used in this study: the Figshare Brain Tumor Dataset. https://www.kaggle.com/datasets/rahimanshu/figshare-brain-tumor-classification and the BraTS2020 (Brain Tumor Segmentation Challenge 2020) dataset, https://www.kaggle.com/datasets/rahimanshu/brats2020-brain-tumor-classificcation to ensure robustness and cross-dataset validation of the proposed models.

The dataset processed by Figshare Brain Tumor Dataset, which can be accessed by the Kaggle platform, is a collection of brain MRI images divided into three clinically important types of tumors: Glioma, Meningioma, and Pituitary tumors. These are the most prevalent brain tumors that are experienced in clinical practice. The dataset includes labeled MRI pictures in JPEG format, each class is placed in a separate folder, and with the help of this, it is possible to extract labels automatically in the preprocessing of data. The images are highly varied in terms of tumor shape, size, intensity, and location, which is a realistic depiction of diagnostic problems in the real world. Due to its ethical sourcing, open access, and previous use in various scholarly studies, the Figshare dataset would be a valid starting point in the implementation of supervised deep learning-based brain tumor classification.

Moreover, the BraTS2020 dataset is used to determine the generalizability of the models on a more complex and richer clinical dataset. BraTS2020 represents a set of multi-institutional and multi-modal brain MRI scans that have been gathered on various clinical sources, such as T1, T1ce, T2, and FLAIR. Although the dataset aims at tumor segmentation, in this case, image-level representations are used in classification tasks, which is in line with the developed methodology. Greater heterogeneity in imaging protocols, in tumor characteristics, and in the acquisition condition is introduced with BraTS2020, which in turn produces a stringent testbed of the model robustness, allowing the comprehensive training, validation, and comparative performance analysis of the model, and supporting the assessment of cross-dataset generalization in brain tumor classification. Figure 2 presents the pre-preparation example MRI images of each group of tumors over the dataset. These crude images indicate the fluctuation of the size, shape, texture, and position of the tumor and hence emphasize the challenge of detecting brain tumors. Subsequent use of preprocessing techniques aids in boosting the performance of models and image quality.

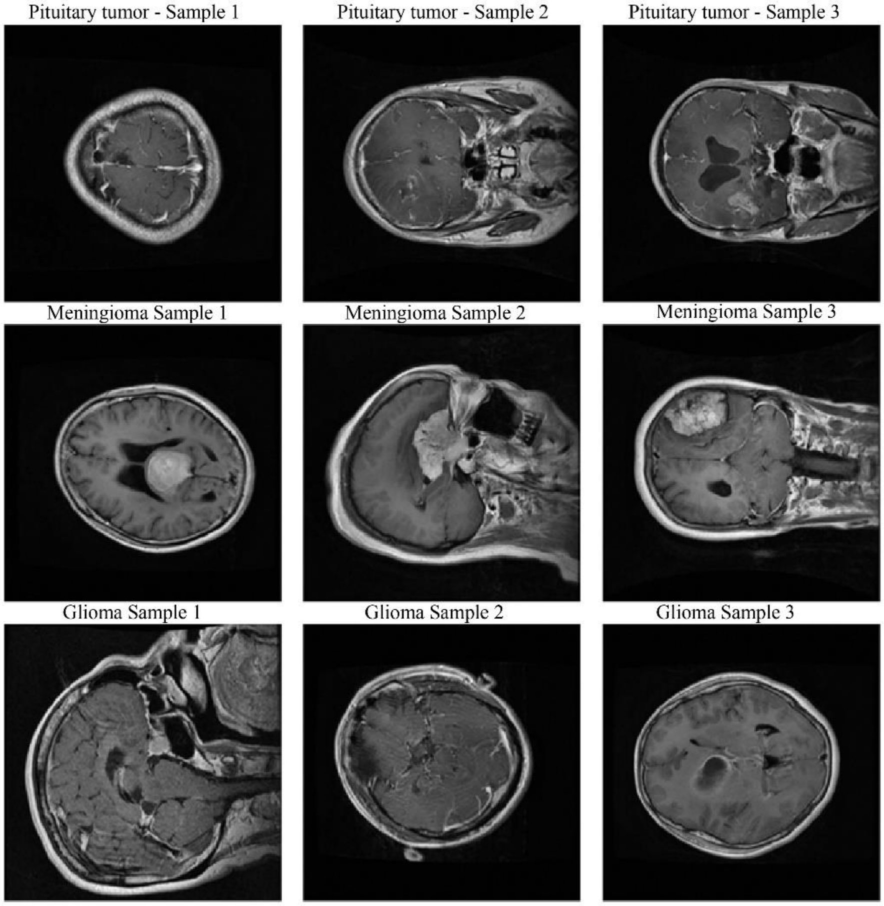

Fig. 2 Sample images from each category in the Fig share dataset before preprocessing

3.2. Data Preprocessing

An effective preprocessing is essential in preparation of the data to be trained in the model. The raw MRI images were preprocessed, and this aided in normalizing the data and improving the performance of the model.

The label names and the directions leading to each JPG image were first extracted automatically from their directory hierarchy. Then, all the photos were grayscale-converted, and important texture and intensity data were maintained, which minimized input complexity and computing cost.

The second thing was to resize the pictures to 224 x 224 pixels, which is the common size of pre-trained multilayer neural networks such as VGG-16. To achieve consistency and stabilize the process of learning the model, the pixel values were rescaled to the [0, 1] range, having been divided by 255 after resizing. In order to maintain the same proportion of classes in the subsets, we have applied stratified sampling to divide the dataset into two halves: 80% train and 20% test. Once the preprocessing was done, intensity distribution graphs were plotted, and sample photographs were made to see the normalization with the naked eye.

The final image is of shape (224, 224, 1). This uniform and exhaustive preprocessing is important to reduce bias due to the different image formats or lighting conditions in order to make sure that the deep learning model acquires meaningful patterns.

Figure 3 displays a randomly selected MRI picture after resizing and normalization. Normalization is applied to ensure the scale of pixel intensity is always within a constant range, and resizing ensures that the size of the images in the set remains constant. These preprocessing processes are important in improving the efficiency of the model, training accuracy, and reducing the cost of computing in the classification.

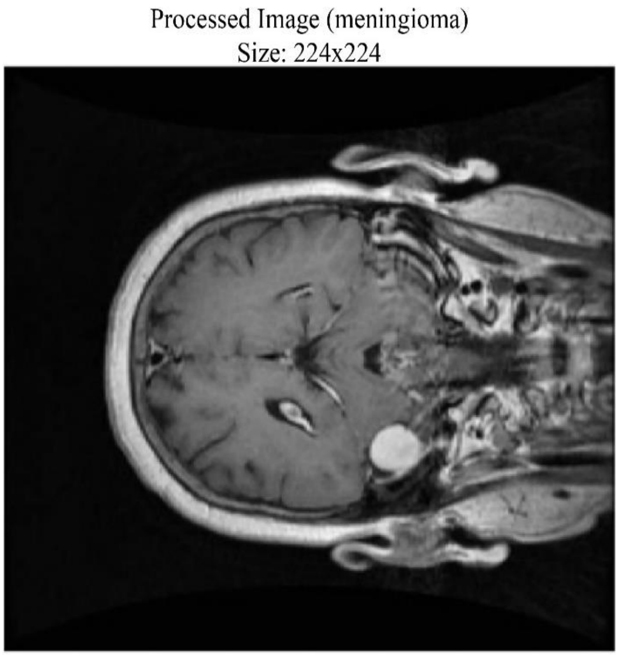

Fig. 3 Random sample image after resizing and normalizing the images of Figshare Data

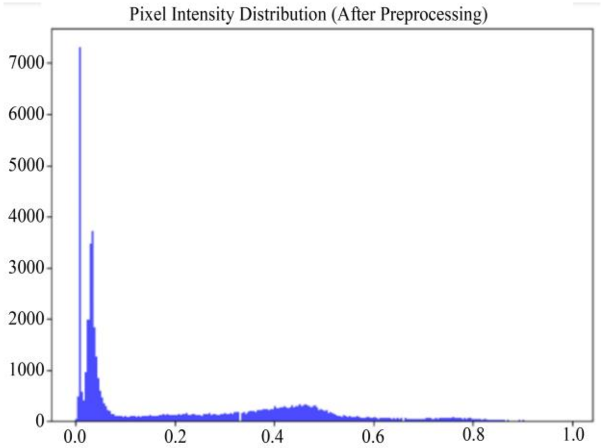

Fig. 4 Image pixel intensity distribution plot (after preprocessing)

Figure 4 displays the after-preprocessing image pixel intensity distribution plot. This plot shows the distribution of the values of pixels in the MRI images after the process of normalization. The distribution is more contrastive and homogenous, and it indicates that preprocessing was effective. This aids the deep learning models in training and infers better.

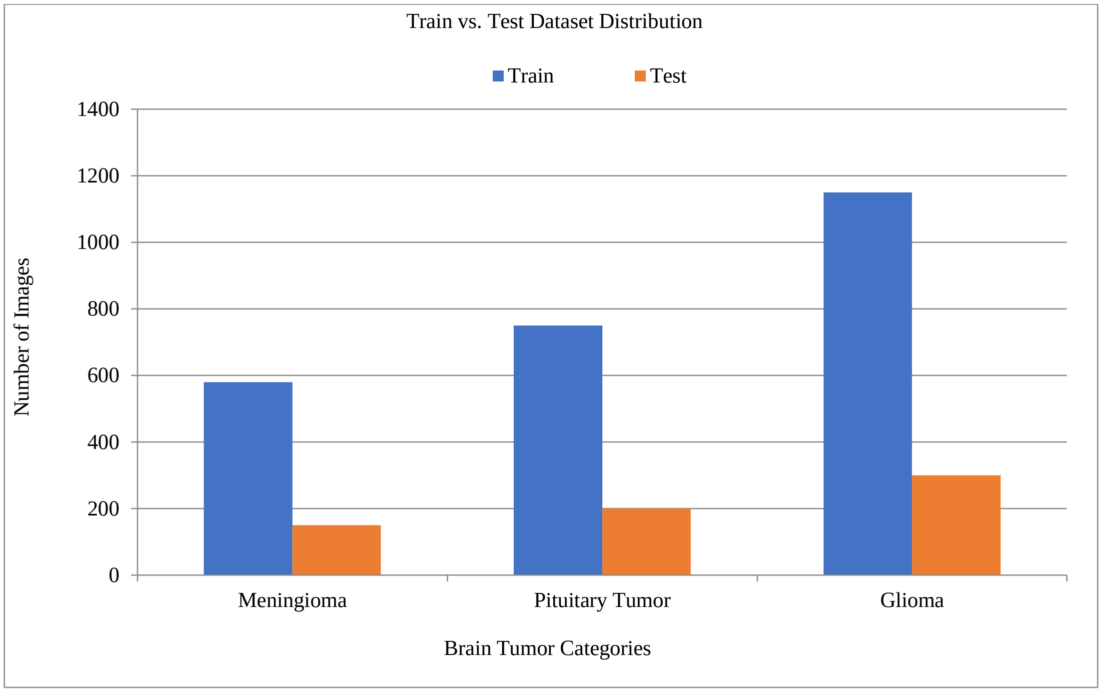

Fig. 5 Dataset distribution after train-test split

Figure 5 is used to display the dataset split between train and test. This graph corresponds to assigning photos to training and testing sets for each type of tumor.

A balanced distribution will ensure that the deep learning model is trained effectively and tested fairly by reducing the risk of bias or overfitting. The localized intensity of the benign tumor is observed in the image, whereas the high background dominance and low high-intensity tumor pixels are observed in the histogram. Normalization of intensities and image resizing by preprocessing makes tumors visible and reduces the background significance, making subsequent deep learning training more reliable and successful.

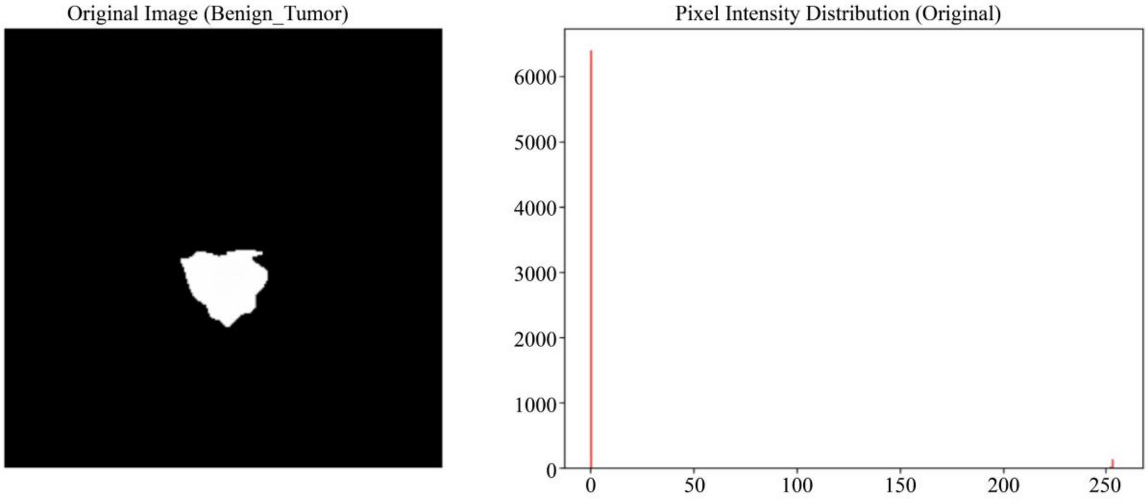

Fig. 6 Pixel intensity distribution of a benign tumor sample from the BraTS2020 dataset

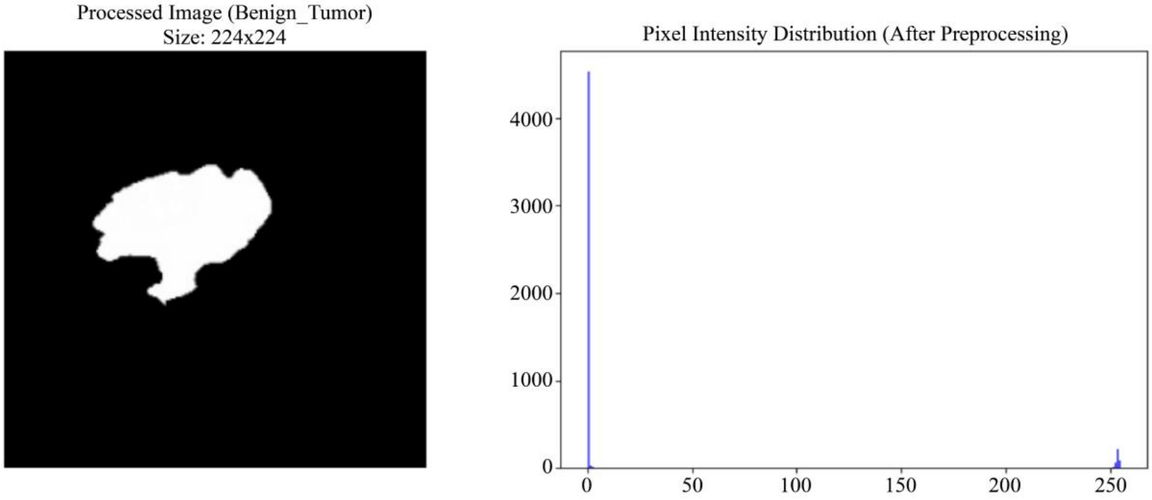

Fig. 7 Preprocessed benign tumor image and corresponding pixel intensity distribution from the BraTS2020 dataset

3.3. Model Implementation

3.3.1. VGG16 Model Implementation

VGG16 was applied with a transfer learning strategy to categorize brain tumor images of the Figshare dataset as benign or malignant, and the Brat2020 Data. The backbone utilized to extract the features was a pretrained VGG16 network that was trained on ImageNet weights. The initial fully connected layers were also eliminated, and a new classification head was implemented, which included a global average pooling layer followed by dense layers comprising ReLU activation and a final layer of global average pooling consisting of a sigmoid or softmax in case of binary classification. The input images were then sized to the needed size, and to make the training stable, they were normalized. Rotation, flipping, and scaling are data augmentation methods that were used to enhance generalization and reduce overfitting. In training, the convolutional base was first frozen to maintain pretrained features, and then fine-tuning on the higher layers was subsequently done to adjust the model to medical imaging properties. Optimization of the model was done by the Adam optimizer based on categorical/binary cross-entropy loss. Accuracy, precision, recall, and F1-score were used to measure the performance. The VGG16 model was found to be effective in extracting features and thus can be used in medical image classification where complex structural patterns are involved.

3.3.2. LeNet + SE Model Implementation

LeNet + Squeeze-and-Excitation (SE) models. It was developed as a simple but powerful architecture for brain tumor classification based on the Figshare dataset. The LeNet architecture base is composed of a series of convolutional and pooling layers, which extract low- and mid-level features, out of input MRI images. SE blocks were added after chosen convolutional layers to make a channel-wise representation of features. These SE modules do a global average pooling followed by full connection layers to recalibrate feature maps by focusing on informative channels and rejecting less informative ones. Training was done on resized and normalized input images. The network itself was trained with the loss of binary cross-entropy and the Adam optimizer. Overfitting was reduced using regularization methods like dropout. Although the depth of the inclusion is relatively shallow, the addition of SE blocks greatly enhanced the discriminative learning so that the model can reflect finer changes of intensity depending on tumor regions. The LeNet + SE model was found to perform better in the Figshare dataset, which shows that through the attention-based channel recalibration, the classification accuracy can be improved significantly, with no substantial impact on the computational efficiency.

3.3.3. ResNet50 Model Implementation

ResNet50 was realized on a framework of deep residual learning in order to solve the problem of vanishing gradients in the training of very deep networks. ResNet50, which is a pretrained model with ImageNet weights, was chosen as a feature extractor for the feature images of the Figshare brain tumor and Brat2020 Data. It has residual connections that enable gradient flow learning and learning multi-level hierarchical representations. The highest classification levels were substituted with a self-made fully connected head that included global average pooling, dense layers, and a last classification one-the preprocessing of the images involved resizing, normalization, and augmentation to enhance robustness. The selective residual blocks underwent fine-tuning to tune the pretrained features to medical imaging data. The Adam optimizer and the cross-entropy loss were used to train the model. The evaluation measures were accuracy, precision, recall, and F1-score. ResNet50 exhibited a high level of generalization as well as constant convergence, which made it a trustworthy model in learning deep spatial information that is important in tumor classification in MRI images.

3.3.4. AlexNet Model Implementation

The AlexNet was used as a Deep Convolutional Neural network consisting of five convolutional layers and fully connected layers to classify brain tumors on Figshare Data and Brat2020 Data. The architecture applies large receptive fields in the earlier stages to obtain coarse spatial features, and the later stages acquire more discriminative representations. Training was done using input images that were resized and normalized.

Nonlinearity was achieved with ReLU activation, and spatial dimensions were reduced with max pooling layers before absent salient features were removed. The fully connected layers were mitigated by dropping out. The Adam optimizer and binary cross-entropy loss were used to train the model. AlexNet was found to have high convergence rates and good classification rates because of its moderate depth and capacity. The fact that it is relatively simple to construct compared to deeper networks makes it computationally efficient, and yet capable of attaining high accuracy when used in medical image classification problems.

3.3.5. EfficientNetB0 Model Implementation

EfficientNetB0 was implemented using a compound scaling strategy that uniformly balances network depth, width, and resolution. A pretrained EfficientNetB0 model was employed for feature extraction on the Figshare dataset. The original classification head was replaced with custom dense layers tailored for binary tumor classification. Input images were resized according to model requirements and normalized.

Data augmentation was applied to enhance robustness. The model was trained using the Adam optimizer with cross-entropy loss. Although EfficientNetB0 is computationally efficient and parameter-optimized, its performance on the Figshare dataset was comparatively lower, potentially due to dataset size, class imbalance, or insufficient adaptation to domain-specific features. Nevertheless, EfficientNetB0 provides a scalable baseline for further optimization and cross-dataset generalization studies.

Table 2. Hyperparameter Comparison Table

Hyperparameter	**VGG16**	**LeNet + SE**	**ResNet50**	**AlexNet**	**EfficientNetB0**
Dataset	Figshare, BraTS2020	Figshare, BraTS2020	Figshare, BraTS2020	Figshare, BraTS2020	Figshare, BraTS2020
Input Image Size	224 × 224 × 3	224 × 224 × 3	224 × 224 × 3	224 × 224 × 3	224 × 224 × 3
Model Initialization	ImageNet Pretrained	Random Initialization	ImageNet Pretrained	Random / Pretrained	ImageNet Pretrained
Convolution Layers	13	2 + SE Blocks	49 + Residual Blocks	5	MBConv Blocks
Attention Mechanism	None	Squeeze-and-Excitation (SE)	None	None	Built-in (MBConv)
Pooling Strategy	Max + Global Avg Pool	Max Pool	Global Avg Pool	Max Pool	Global Avg Pool
Fully Connected Layers	Custom Dense Layers	Dense Layers	Custom Dense Layers	Dense Layers	Custom Dense Layers

Activation Function	ReLU	ReLU	ReLU	ReLU	Swish
Output Activation	Sigmoid / Softmax	Sigmoid	Sigmoid / Softmax	Sigmoid	Sigmoid
Loss Function	Binary Cross-Entropy	Binary Cross-Entropy	Binary Cross-Entropy	Binary Cross-Entropy	Binary Cross-Entropy
Optimizer	Adam	Adam	Adam	Adam	Adam
Learning Rate	0.0001	0.0001	0.0001	0.0001	0.0001
Batch Size	16 / 32	16 / 32	16 / 32	16 / 32	16 / 32
Number of Epochs	20–30	20–30	20–30	20–30	20–30
Dropout Rate	0.5	0.5	0.5	0.5	0.5
Data Augmentation	Rotation, Flip, Zoom	Rotation, Flip	Rotation, Flip, Zoom	Rotation, Flip	Rotation, Flip, Zoom
Fine-Tuning	Yes (Top Layers)	No	Yes (Last Blocks)	No	Yes (Top Layers)
Evaluation Metrics	Accuracy, Precision, Recall, F1-score	Accuracy, Precision, Recall, F1-score	Accuracy, Precision, Recall, F1-score	Accuracy, Precision, Recall, F1-score	Accuracy, Precision, Recall, F1-score

Previous research often used random hyperparameter configurations, which limited the scope of generalization. Standardization of hyperparameters in the current paper was done in a systematic manner and empirically verified by various repetitions of experiments, i.e., robustness, stability of convergence, and performance improvements were obtained across various model architectures.

3.3.6. Adam Optimization

Adam is a technique whose general value includes that of the RMSprop optimization technique and momentum. The angle update equation of 3 in Adam optimization is calculated through the subsequent calculation:

$$\theta_{t+1} = \theta_t \frac{\alpha \cdot m_t}{\sqrt{v_t + \epsilon}} \tag{1}$$

Parameters of the model are denoted by theta, learning rate by alpha, exponentially decaying average of historical gradients by m t, exponentially decaying normal of historical squared gradients by v t, and systems division by zero by epsilon, using the method of optimizing updates in Adam with its small constant.

3.3.7. ReLU

Common to neural networks is the rectified linear unit, also known as ReLU, which delivers the present value directly forward should the input be positive; it is zero should the input be negative.

ReLU develops activation sparsity and works to address the vanishing gradient issue during training. Deep learning systems pick this traditional solution since they are simple and effective.

$$f(x) = \max(0, x) \tag{2}$$

The x is the input of a function; that is, the output is f (x). The ReLU operation is either a zero or a positive (x) input operation. This simple piecewise-linear function is largely relied upon in the training of neural networks because neural networks promote sparsity and reduce the impact of the vanishing gradient problem.

3.3.8. Softmax

Softmax is a simple component of neural networks since it allows standardizing the scores based on the input. The exponential is divided by the sum of all the exponentials to calculate each of the input values. The normalizing technique ensures that the value of the outputs is between zero and one, and thus gives one an opportunity to represent probability appropriately. The softmax is useful in making problems based on classification less difficult, as now the result of the network can be viewed as the likelihood of each class. In machine learning, tasks are based on projections by neural networks, and softmax is a necessary tool to transform the projections into useful probabilities.

$$\mathbf{softmax}(\mathbf{x_i}) = \frac{\mathbf{e^{xi}}}{\sum \mathbf{j} \mathbf{e^{xj}}} \tag{3}$$

4. Result & Discussion

4.1. Accuracy

Uses the correct projections to calculate the total prediction ratio to deduce the overall model accuracy.

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{4}$$

4.2. Precision

Stresses that minimize the false positives by depicting all the anticipated positives, and the proportion of correctly predicted outcomes.

$$Precision = \frac{TP}{TP+FP} \tag{5}$$

4.3. Recall

Demonstrates the ability of the process to detect the true positives, as it shows the percentage of true positives that have been correctly identified.

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

4.4. Loss

Computes the differences between anticipated and actual values, therefore guiding the model optimization by minimizing training errors.

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{y}i.\log(\mathcal{y}i) \tag{7}$$

The score on the Figshare dataset shows that VGG16 and ResNet50 are the most accurate, with the highest score of 93.31, and this indicates a high overall performance of classification.

They are, however, very low in terms of their precision, recall, and F1-scores (around 3537%), meaning that the models are not very good at correctly classifying positive cases or breaking the class imbalance.

AlexNet has a little lower accuracy (89.89) and has a comparable low F1-score, whereas EfficientNetB0 has worse accuracy (46.88), even though it has a better recall, indicating that it is predicting positives too broadly. LeNet demonstrates average results (accuracy 61.17%). In general, VGG16 has a slightly higher F1-score than others; thus, it is the best-balanced model in this task.

Table 3. Results of Proposed Models on Figshare data

Model	Accuracy	Precision	Recall	F1-score
VG16	93.31	37.11	37.19	37.15
ResNet50	93.31	35.77	35.89	35.83
AlexNet	89.89	36.07	34.91	35.41
EfficientNetB0	46.88	21.97	46.88	29.92
LeNet+SE	61.17	35.81	32.14	32.10

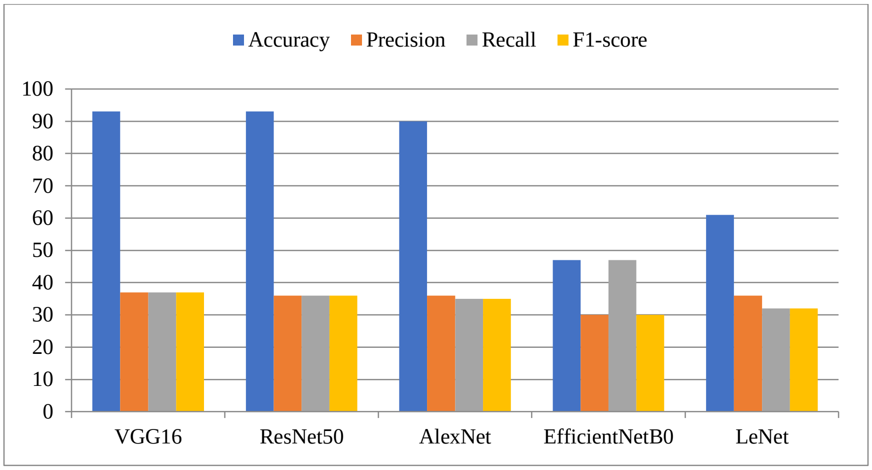

Fig. 8 Performance Evaluation Graph of Proposed Models on Figshare Dataset

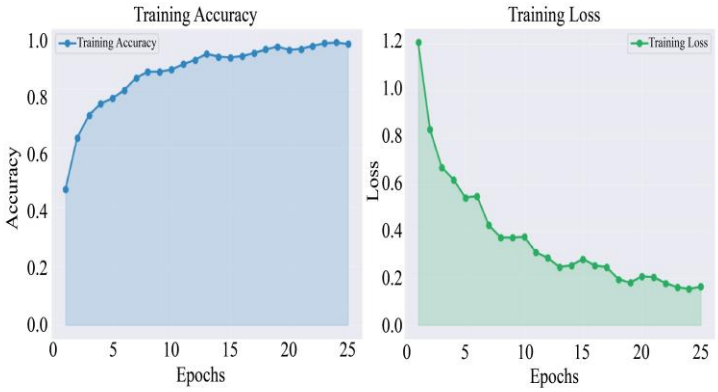

Fig. 9 Training Accuracy and Loss Graph

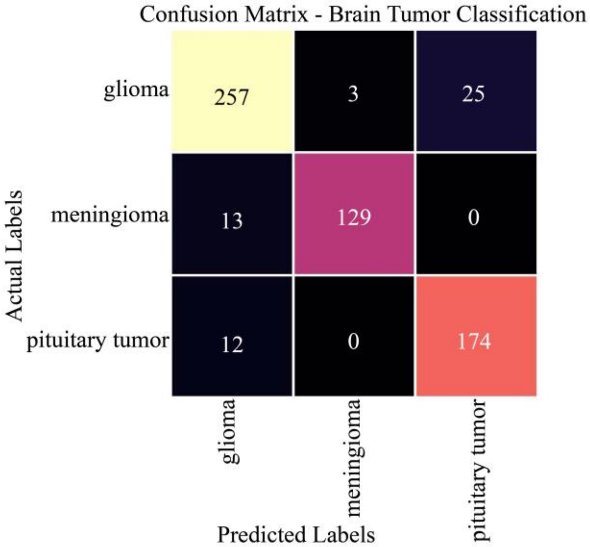

Fig. 10 Confusion Matrix of VG16

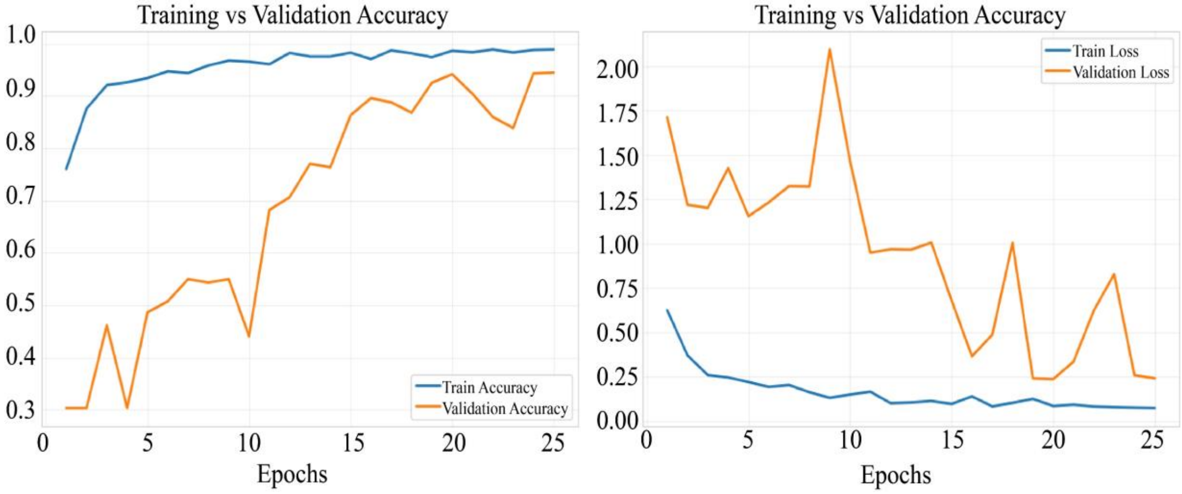

Fig. 11 Training vs Validation Accuracy and Loss of Resnet 50

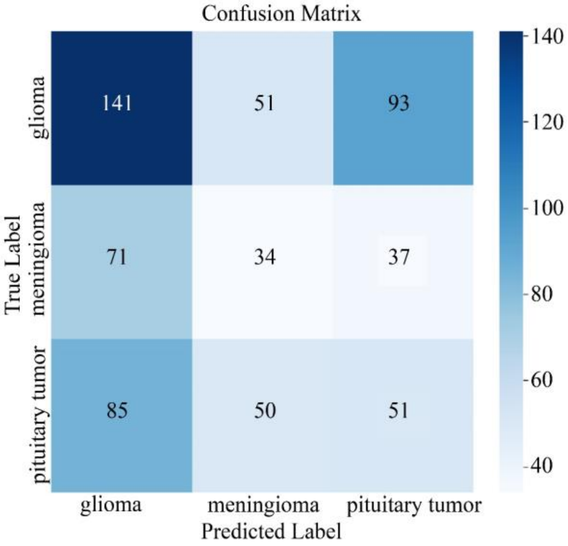

Fig. 12 Confusion Matrix of ResNet50

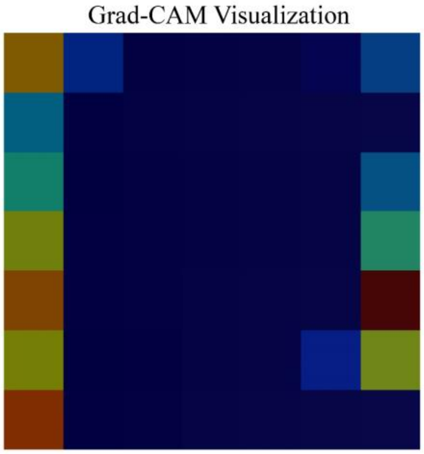

Fig. 13 Grad-CAM Visualization on Figshare data

The Figshare dataset was analyzed using Grad-CAM visualization to study the image regions that produced the greatest impact on the decisions of the model to classify them as either benign or malignant. The warm colors (yellow, red) in the produced heatmaps represent the areas that have a significant impact on the prediction of the model, whereas the cold ones (blue, dark colors) show those with low or no contribution. The fact that the large dark-blue region is in the middle of the images indicates that the model did not focus much on the central image appearances, and the central pixels played a small role in the final determination. On the whole, according to the Grad-CAM outputs, the focus of the model is concentrated more at the edges of the image than at the tumor region in the middle of the image. This trend suggests a possible reliance on peripheral image characteristics or acquisition artifacts, and stronger measures to ensure the use of clinically significant features should include region-specific learning approaches and stronger preprocessing approaches. The LIME description of the VGG16 model is that the most significant superpixel areas are mainly localized around structural edges, which shows that the model is mostly dependent on the shape and edge-related characteristics in the process of distinguishing the benign and malignant tumors. It is spatial localization, but the core of the tumor is not wholly focused in the model, and it can be implied that the attention relies partially on the contextual image characteristics, instead of focusing on the tumor alone. It should be mentioned that the tumor segmentation was not done in the given study because pixel-level annotations were not present in the dataset, and, as such, the study was done on image-level classification with the segmentation as a direction to further research. Furthermore, to resolve the issue of data privacy and ethical issues in medical imaging, a federated learning architecture is conceptually offered, where each hospital trains a local model with the help of private MRI data and submits only the weights of the learned models to a central server, which averages them through Federated Averaging (FedAvg), and thus collaboratively learns without being exposed to raw patient data.

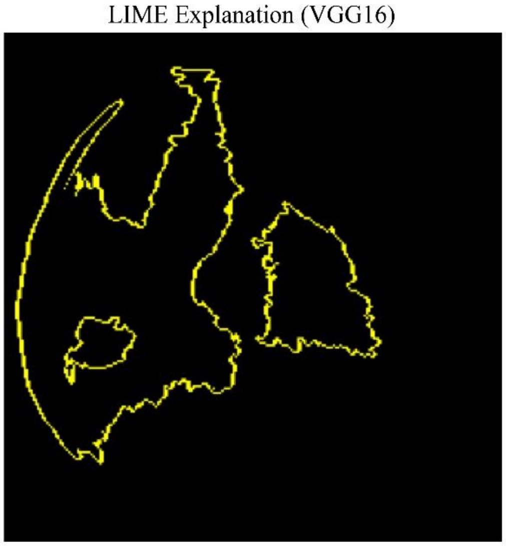

Fig. 14 LIME

Table 4. Results of Proposed Models on Brats2020 Data

S. No.	Model	Accuracy	Precision	Recall	F1-Score
1	VGG16	93.48	93.10	93.48	92.85
2	LeNet + SE	98.44	98.43	98.44	98.43
3	ResNet50	94.45	94.22	94.45	94.29
4	AlexNet	97.58	97.56	97.58	97.57
5	EfficientNetB0	93.00	91.00	73.00	79.00

The findings show that the LeNet + SE model is most effective in terms of all evaluation measures, showing the efficiency of squeeze-and-excitation blocks to improve feature representation.

ResNet50 and VGG16 perform competitively but with comparatively better scores than AlexNet. EfficientNetB0 has low recall and F1-score, which demonstrates that it is limited to detecting malignant cases with BraTS2020. Through this Grad-CAM visualization, one can see the areas of the MRI image of the Brat2020 data, which has most likely changed the decision of the EfficientNetB0 model. The model assigned the correct label either Benign Tumor to the sample as shown by the congruence between the true and the predicted labels. The identified areas depict spatial areas on which the network concentrated its attention and in which it made the prediction. The relatively localized and mild intensity activation indicates that the model was based on subtle and localized structural characteristics and not aggressive and extensive patterns of abnormality, which is also in line with the nature of benign tumors. Such visualization enhances the interpretability of models as it effectively demonstrates that the medicine-relevant image regions are used to make a prediction instead of random background data.

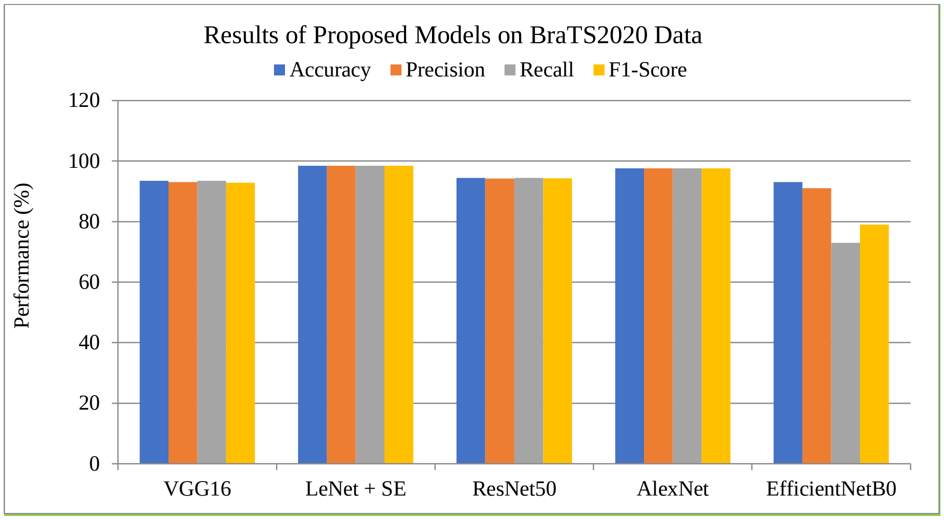

Fig. 15 Performance Evaluation Graph

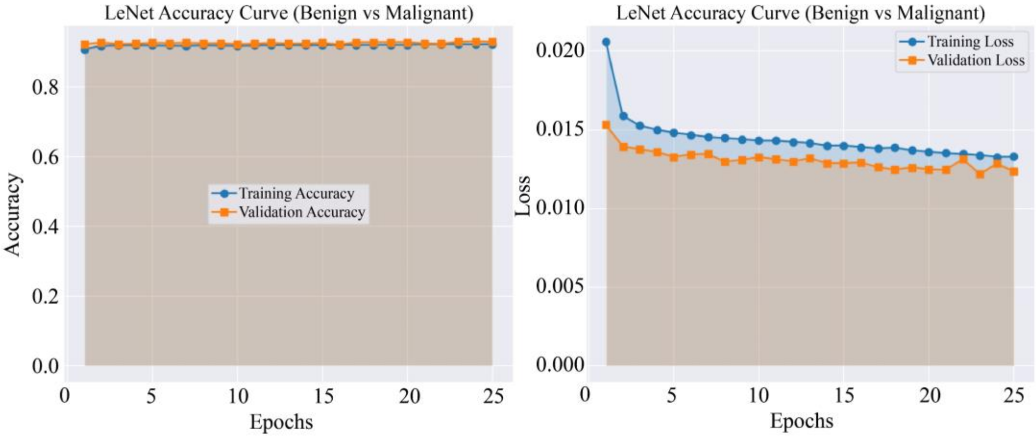

Fig. 16 Accuracy and Loss curve of LeNet+SE

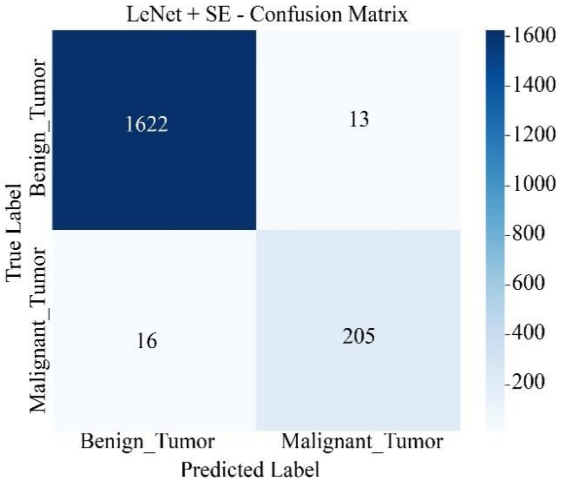

Fig. 17 Confusion Matrix of LeNet +SE

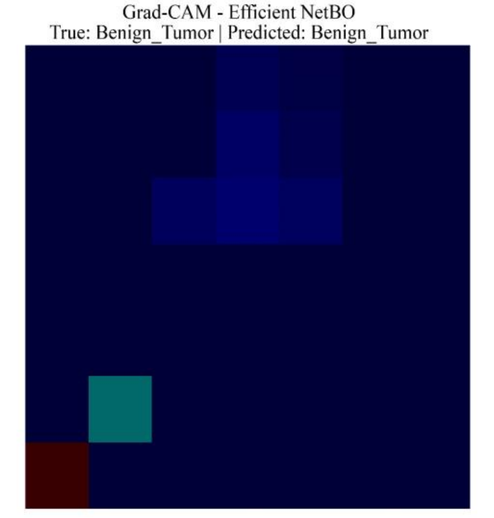

Fig. 18 Grad-CAM (EfficientNetB0) Brat2020 data

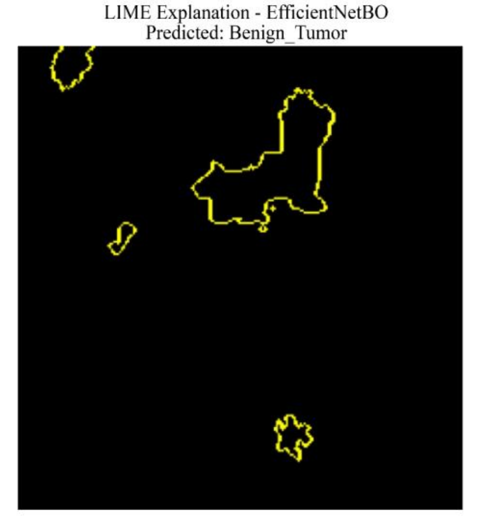

Fig. 19 LIME (EfficientNetB0) of Brat2020 data

This LIME description brings out the particular image areas that contributed the most to the EfficientNetB0 model's prediction of Benign Tumor of Brat2020. The yellow-filled superpixels reflect the areas that have made a positive impact on the classification choice.

These regions are associated with localized structural patterns in the MRI image that the model finds significant in the identification of benign characteristics. The fact that no big highlighted areas are observed implies that the model was based on a few meaningful features as opposed to the noise or background areas.

Altogether, this visualization makes the interpretation process easier as it illustrates that the prediction is guided by the parts of images that used to be relevant, and it is more difficult to doubt the model's decision-making process. Table 4 obviously shows that the suggested LeNet + SE model on the BraTS2020 data set is more effective in classification accuracy than the existing models. Whereas ResNet-50 and U-Net have an accuracy of 81.6 percent and 88.8 percent, respectively, the proposed method has a far higher accuracy of 98.44 percent, which implies that it has a better discriminative performance. The latter can be explained by the fact that Squeeze-and-Excitation (SE) blocks have been integrated into the LeNet architecture, and they improve the channel-wise feature recalibration and enable the model to concentrate on the most informative tumor-related features. Moreover, LeNet is also lightweight, and the attention-based SE modules prevent overfitting and enhance generalization. Therefore, the proposed model has been shown to be more robust and effective in the classification of brain tumors on BraTS2020 data.

Table 5. Comparative Analysis between Existing Models and Proposed

Models	Accuracy	References
ResNet-50	81.6	[41]
U-Net	88.8	[42]
Proposed LeNet +SE on Brats2020 Data	98.44	------

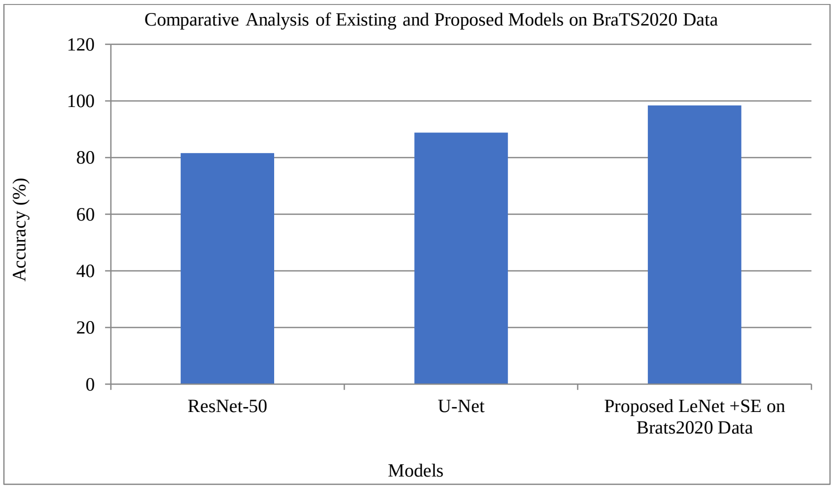

Fig. 20 Comparative Analysis

5. Conclusion

This paper introduced a powerful and explainable deep learning model to classify brain tumors using MRI images and overcome the important drawbacks of the current methods regarding their external validity, complexity, and clarity. The suggested methodology overcomes the limitation of dependence on a single dataset and contributes to a more accurate evaluation of model performance under different imaging conditions by using two heterogeneous public datasets, Figshare and BraTS2020. Fair benchmarking and reproduction of all the evaluated models was made possible by the use of a common preprocessing pipeline and a standard set of hyperparameters. The greatest contribution of the work is the adoption of the Squeeze-and-Excitation (SE) attention mechanisms and integrating them into a lightweight LeNet architecture. This architecture is useful in improving feature discrimination on a channel-by-channel basis and is still computationally efficient. It has been shown that attention mechanism-enhanced shallow networks can outperform or even be more efficiently trained than deeper models that consume more resources. The success of the proposed approach was further confirmed by comparing it with known CNN architectures, such as VGG16, ResNet50, AlexNet, and EfficientNetB0, as well as their use in the context of the same experiment. Also, the integration of explainable AI, e.g., Grad-CAM and LIME, enhanced model transparency, as it gave a visual understanding of the areas of decisions that were made, thus facilitating more clinical trust and interpretability. The results in general support the hypothesis that attention-enhanced lightweight architectures, cross-dataset validation, and explainable learning are a viable and scalable solution in automated brain tumor classification. This architecture provides a solid basis for future extensions in the areas of segmentation, federated learning, and clinical deployment.

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