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Transfer Learning and Advanced CNN Models for Detecting Brain Tumors using MRI

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ABSTRACT

This paper explores the efficacy of three advanced deep convolutional neural network (CNN) models; DenseNet, MobileNet, and Xception in classifying brain tumors from MRI scans. Accurate detection and classification of brain tumors are critical for timely medical intervention, and recent advancements in deep learning offer promising tools for this task. We apply each model to a publicly available brain tumor dataset, evaluating their performance in terms of accuracy, sensitivity, specificity, and computational efficiency. The experiments utilize the well-known Brain Tumor Classification dataset, consisting of 3264 MRI images categorized into glioma, meningioma, pituitary tumor, and non-tumor classes. The results demonstrate that each model has unique strengths, with DenseNet showing superior accuracy, MobileNet excelling in computational efficiency, and Xception achieving a balance of both but better than others. The Xception achieved the most suitable performance with an accuracy of 97.6%, sensitivity of 97.9%, precision of 98.5%, specificity of 97.2%, and an F1-score of 97.9%. These results show that Xception excels over other architectures, making it highly effective in classifying abnormal and normal tumors from brain MRI images. Our findings highlight the importance of model selection based on specific clinical requirements and computational constraints and suggest pathways for further research and optimization in medical image analysis.

Keywords: Brain Tumor Classification, Dense Net, Mobile Net, MRI, Medical Imaging, Xception.

1. INTRODUCTION

AI is revolutionizing medical treatment by enhancing diagnostic accuracy, predicting patient outcomes, and optimizing treatment protocols for Coronavirus, depression, dental services, and pregnancy to heart and types of brain diseases (Afrazeh, F. 2024, Afrazeh, F. 2024, Ghasemi, Y. 2024, Nafissi, N. 2024, Akhoondinasab, M.2024, Norouzi, F. 2024, Mahmoudiandehkordi, S. 2024, Minoo, S. 2024, Orouskhani, M. 2022, Abbasi, H. 2024). It analyzes imaging data and tailors personalized treatment plans, ultimately improving patient care with precision and effectiveness. Brain tumors, often resulting from malfunctioning neurons, rank among the most common types of cancer. The importance of prompt and precise diagnosis cannot be overstated. Diagnostic techniques like computed tomography (CT) scan, positron emission tomography (PET), and magnetic resonance imaging (MRI) are utilized to efficiently aid physicians in diagnosing tumors. However, MRI plays a crucial role in brain tumor detection and care as it enables clinicians to locate precisely, assess the extent, and identify different types of tumors. This information is vital for initial diagnosis and treatment planning, Brain tumors exhibit considerable diversity in size, shape, type, and position (Asiri, A. 2023).

Gliomas are tumors originating from glial cells in the brain or spinal cord, with varying levels of aggressiveness (Louis, D. 2016). Meningiomas, which develop from the meninges, are generally benign but can cause neurological symptoms due to their pressure on brain structures (Claus, E. B. 2005). Pituitary tumors, arising in the pituitary gland, impact hormone production, and can lead to symptoms like headaches and vision problems (Asa, S. L. 2009). Each tumor type requires precise diagnosis and tailored treatment strategies. See Figure 1.

MRI uses strong magnetic fields and radio waves to generate detailed images of organs and tissues in the body. It's instrumental in detecting abnormalities in the brain because it can distinguish between different types of brain tissue, including gray matter, white matter, and cerebrospinal fluid. This detail level helps doctors precisely identify tumors, strokes, and other conditions. However, manual interpretation of MRI scans depends on radiologists' expertise, presenting challenges such as time consumption and susceptibility to human error, which ultimately affect diagnostic accuracy and treatment planning. (Albalawi, E. 2024)

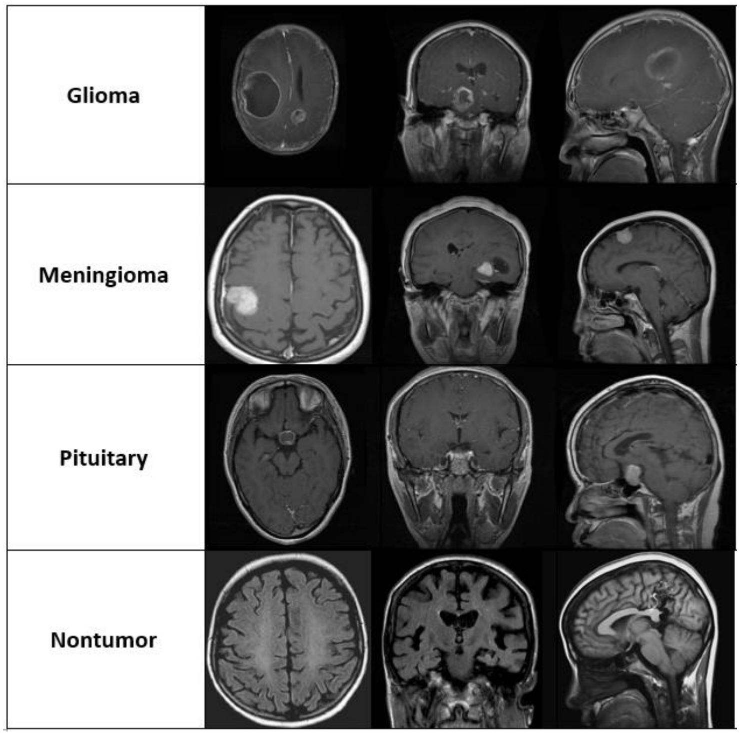

Figure1: Types of Brain Tumor (Created by Author from Dataset)

The scientific investigation of brain tumor segmentation and classification via neuroimaging techniques has become increasingly crucial due to the high risk associated with undiagnosed tumors. Accurate classification enables healthcare providers to administer suitable treatments, with deep learning methods, especially convolutional neural networks (CNN), demonstrating considerable efficacy in these applications (Kumar, S. 2023).

A study introduces an intelligent system for automatically extracting and identifying brain tumors from 2D CE MRI images to improve diagnosis and treatment. It utilizes a two-stage approach: segmentation of tumors using an encoder-decoder U-net with the residual network, achieving high accuracy (99.60%), sensitivity (90.20%), and specificity (99.80%), followed by classification of tumors with a YOLO2-based transfer learning approach, which achieves a 97% classification accuracy. While the method outperforms current techniques, potential limitations include dataset diversity and computational resource requirements (Sahoo, A. K. 2023). Another study presented a novel Convolutional Neural Network (CNN) architecture aimed at improving the accuracy and efficiency of brain tumor detection in MRI scans. Using a dataset of 7,023 brain MRI images, the study employs a multi-task classification model for detecting, classifying, and locating brain tumors, achieving a remarkable 99% classification accuracy. However, the study notes the need for more diverse training datasets, improved model interpretability, and extensive clinical validation to enhance the model's generalizability and clinical utility (Albalawi, E. 2024). Sarkar et al employed a 25-layer CNN model to classify brain tumors using public MRI datasets, demonstrating improved performance over earlier methods, with 86.23% and 81.6% accuracy depending on the optimizer used. However, challenges persist in advancing real-time processing and integrating the model into clinical workflows. (Sarkar, A. 2023)

Lastly, a study highlights the significant advancements in ischemic stroke segmentation and marks CNNs and U-Net-based architectures as the best deep learning models. These models excel in accurately and automatically identifying ischemic stroke lesions from MRI and CT data, handling the complexity and variability of lesions through large-scale dataset training. They demonstrate strong generalization capabilities across different imaging modalities, making them

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suitable for diverse clinical settings. However, challenges remain in improving the models' robustness and integrating them seamlessly into routine clinical workflows for widespread adoption. (Abbasi, H. 2023)

Exploring previous works demonstrated that deep convolutional neural network (CNN) models outperformed other approaches. To address their shortcomings, our research incorporates DenseNet, MobileNet, and Xception architectures for classifying brain tumors from MRI scans using the well-known Brain Tumor Classification dataset. This approach aims to compare the accuracy, efficiency, and generalizability of tumor detection and classification to identify the best solution for classifying brain tumors, effectively addressing issues of late or incorrect diagnosis with high efficiency and accuracy.

DenseNet (Densely Connected Convolutional Networks), MobileNet, and Xception are three innovative deep-learning architectures utilized for brain tumor classification in MRI scans. DenseNet enhances feature propagation and reuse by connecting each layer to every other layer in a feed-forward manner, achieving high accuracy with fewer parameters (Huang, G. 2017). MobileNet, designed for mobile and embedded vision applications, employs depth-wise separable convolutions to significantly reduce the number of parameters and computational costs, making it suitable for real-time applications on resource-limited devices (Howard, A. G. 2017). Xception, or Extreme Inception, replaces Inception modules with depth-wise separable convolutions, offering improved performance with a similar number of parameters. These architectures collectively enhance the robustness and adaptability of brain tumor classification models across various imaging settings, contributing to their practical utility in diverse clinical environments. (Chollet, F. 2017)

2. RELATED WORK

MRI scans offer crucial details about a brain tumor’s size, shape, type, and location. Among the most perilous types detected through MRI are gliomas and meningiomas. Early detection is vital, as failure to identify these tumors promptly can result in severe health consequences or death (Ghassemi, N. 2020). In many cases, the brain tumor size is slightly different in color concentration, form, and surface. The famous institute, the World Health Organization (WHO), categorizes the tumor into four grades. Grade I and II are the lower level of brain tumors known as meningioma, and grades III and IV are identified as a more severe type of tumor-like glioma (Asiri, A. A. 2023). So, the classification of tumors is a vital component in the treatment procedure.

Artificial intelligence, particularly convolutional neural networks (CNNs), has significantly advanced the field of medical imaging for brain tumor diagnosis from MRI scans. This section explores recent methodologies, highlighting both their contributions and limitations, and sets the stage for presenting the proposed method. At first, Support Vector Machines (SVMs) and Random Forests as traditional techniques were employed, which relied on expert-driven feature extraction and often missed dynamic feature-learning capabilities and critical details (Alzubaidi, L. 2021). Early CNN models, limited by computational constraints, struggled to capture complex features. More advanced architectures, such as AlexNet and VGG, enhanced feature extraction but encountered issues like overfitting and the requirement for large, labeled datasets (] Albalawi, E. 2024). Transfer learning mitigated data scarcity by refining models initially trained on extensive datasets like ImageNet. Incorporating multimodal MRI data enhanced analytical accuracy, yet synchronizing features from diverse modalities proved challenging (Ahmmed, S. 2023). Attention mechanisms improved interpretability by highlighting relevant regions, whereas 3D CNNs maintained spatial relationships for volumetric analysis, albeit with increased computational complexities (Aboussaleh, I. 2023). Ensemble learning enhanced accuracy, albeit with heightened computational demands, while domain adaptation sought to generalize models across various MRI scanners and protocols (Zhao, R. 2023).

The overview of some recent studies is presented here:

Minarno et al. employed a CNN to detect types of brain tumors in MRI images, analyzing a dataset that includes more than 3000 high-resolution images (Minarno, A. E. 2021). Their CNN approach, combined with Hyperparameter Tuning, aimed to optimize classification results, achieving a 96.00% accuracy in the third evaluation scenario. Using various deep transfer learning models like DenseNet201, DenseNet169, DenseNet121, MobileNet v2, VGG19, VGG16, and Xception, their study focused on developing a brain tumor detection model. DenseNet201, in particular, showed superior performance with a training accuracy of 97.49% and a validation accuracy of 96.43% (Rajak, P.

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2023). Habiba et al. used deep learning classifiers, specifically InceptionV3 and DenseNet201, and data augmentation to improve classification accuracy. The proposed Brain-DeepNet model achieved a 96.3% accuracy. (Habiba, S. U. 2022).

Rahman introduced a Parallel Deep Convolutional Neural Network (PDCNN) topology to address overfitting issues in brain tumor classification from MRI images by extracting both local and global features (Rahman, T. 2023). Utilizing dropout regularization and batch normalization, along with resizing, grayscale transformation, and data augmentation, the PDCNN effectively combines two CNNs with different window sizes. Tested on three datasets and achieved high accuracies of 97.33%, 97.60%, and 98.12% for binary and multi-class classifications. Despite its efficiency and precision, more work is needed to implement a 3D structure for enhanced tumor identification from 3D MRI images. Nancy et al introduced an advanced Brain Tumor Segmentation and Classification (BTSC) model utilizing a transfer learning-based CNN, specifically the VGG-19 model. It employed various image augmentation techniques and an Attribute Aware Attention (AWA) methodology to enhance feature extraction, leading to impressive classification accuracies of 96.20%, 98.20%, and 99.40% across BRATS 2019, 2020, and 2021 datasets. Despite these results, limitations include the need for diverse datasets to ensure generalizability and the computational demands of the model, which may hinder widespread clinical implementation (Nancy, A.M. 2024).

Akter proposed a deep CNN architecture for automatic brain tumor classification. It also employs a U-Net-based segmentation model (Akter, A. 2024). Tested on six benchmark datasets, the classification model achieved the highest accuracy of 98.7%, improving slightly with segmentation (98.8%). While the proposed model outperforms existing pre-trained models, challenges remain in dataset augmentation and the need for more real-life MRI data to enhance segmentation and training processes. Another addresses the challenge of early and accurate brain tumor detection by proposing a framework using multiple CNN models with transfer learning and fine-tuning, combined via a particle swarm optimization algorithm. Tested on three datasets, the model achieved high classification accuracy (99.35%, 98.77%, 99.92%) and F1-scores (Çetin-Kaya, Y. 2024).

Tandel explored non-invasive MRI-based CAD tools for brain tumor grading to avoid the risks associated with biopsies. It uses three MRI sequences (T1W, T2W, FLAIR) and five CNN models (AlexNet, VGG16, ResNet18, GoogleNet, ResNet50) for classifying gliomas (Tandel, G. S. 2023). An ensemble algorithm, based on majority voting, improved classification accuracy across datasets, with FLAIR-MRI data achieving the highest accuracy of 98.88%. Mahmud et al represented a CNN architecture for efficient brain tumor identification, using MRI images, comparing its performance with models like ResNet-50, VGG16, and Inception V3. Analyzing 3264 MR images, the proposed CNN model achieved an accuracy of 93.3%, an AUC of 98.43%, a recall of 91.19%, and a loss of 0.25. While the model shows promise for early brain tumor detection, the study highlights the challenges of long training times due to limited GPU capabilities and large datasets. Future research aims to enhance detection accuracy by incorporating individual patient data (Mahmud, M. I. 2023). Talukder introduced a technique for classifying brain tumors by leveraging various pre-trained models. Their approach led to an impressive accuracy of 99.68% when using ResNet50V2. However, the study had a notable limitation due to the lack of sharp images, which could impact the precision of their classification results. Despite this, the high accuracy achieved demonstrates the potential effectiveness of their method (Talukder, M. A. 2023).

Another study explored automating brain tumor classification using the DenseNet architecture to improve diagnostic accuracy and generalizability. Using the Figshare dataset with 3,064 MRI images, DenseNet outperformed ResNet, EfficientNet, and MobileNet, achieving 97.1% accuracy after fine-tuning. The study emphasizes the model's robustness, with precision, recall, and F1-scores all exceeding 0.94. However, the research highlights the need for further validation of diverse clinical datasets and individual analysis of regularization techniques to enhance the model's reliability and generalizability (Aziz, N. 2024). Reddy et al evaluated Fine-Tuned Vision Transformer (FTVT) models for brain tumor classification using a dataset of 7,023 MRI images categorized into four classes. They compared FTVT models (FTVT-b16, FTVT-b32, FTVT-l16, FTVT-l32) with ResNet-50, EfficientNet-B0, and MobileNet-V2, the FTVT-l16 achieved the highest accuracy of 98.70%. The study highlighted FTVT models' robustness and accuracy, outperforming other deep learning models. However, future work should explore individual

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impacts of regularization techniques and validation on diverse clinical datasets to enhance model reliability (Reddy, C. K. K. 2024) further.

Another study introduces a hybrid deep transfer learning model (GN-AlexNet) for brain tumor classification, combining GoogleNet and AlexNet architectures. The model was tested on the CE-MRI dataset and compared with various transfer learning techniques, achieving superior accuracy (99.51%) and sensitivity (98.90%). The findings highlight the model's robustness and efficiency in classifying pituitary, meningioma, and glioma tumors. However, further validation on diverse data types and larger datasets is needed to confirm its generalizability and performance in different clinical scenarios (Samee, N. A. 2022). Another one focuses on accurately classifying different brain tumors using the Xception architecture, which involves flattening, dropout, and dense layer operations to extract features based on shapes, spatial relationships, and structures. Evaluated on a dataset of 7023 MRI images, the proposed method achieved over a 90% average classification rate, outperforming existing approaches. The model also demonstrated robustness to noise and blur in the data. However, challenges remain in handling complex background images and improving classification accuracy in diverse clinical settings (Thakur, A. 2024). Cobilla et al leveraged deep learning techniques, specifically CNNs, data augmentation, and image processing, to classify brain MRI scans as cancerous or non-cancerous and t. They compared primary CNN models to pre-trained CNN and Xception models, the researchers achieved 96% accuracy with the Xception model. However, the study's limitation lies in its use of a limited dataset, which may affect the generalizability of the results (Cobilla, R. 2023).

Although these advancements have been significant, challenges persist, especially in analyzing brain MRI scans. The intricate nature of brain anatomy and the varied presentations of tumors necessitate a customized approach to AI model development. Our study focuses on this specialized area, evaluating three CNN architectures designed specifically for the complex task of detecting brain tumors in MRI images. By refining and advancing CNN capabilities within this specific context, our research aims to set a new benchmark in accuracy and efficiency for diagnosing brain tumors, thereby pushing the boundaries of AI in medical imaging.

3. METHODOLOGY

CNNs utilize several key architectural components such as convolutional layers, pooling layers, activation functions, and other critical elements to examine MRI scans, differentiating tumor types and providing vital diagnostic information. By investigating various CNN models including Xception, MobileNet, and DenseNet. Each model was selected for its unique structural benefits and track record in image classification tasks. This research aids in the progression of deep learning to precisely classify brain tumors to improve medical services.

3.1 Model Architecture

DenseNet is a modified standard CNN, known for its dense connectivity pattern, where each layer receives input from all previous layers, enhancing information flow and gradient propagation. Figure 2 represents the DenseNet structure.

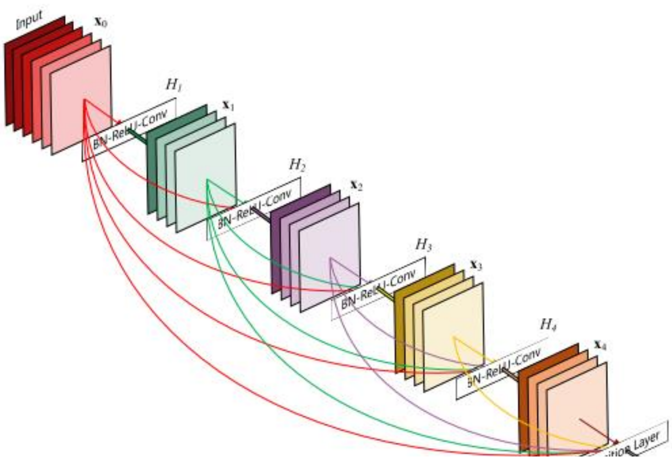

Figure2: DenseNet architecture (Zhang, L.2020)

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MobileNet is an optimized CNN architecture, designed to reduce computational load through specialized convolutions. It maintains competitive accuracy while minimizing memory usage, making it well-suited for resource-constrained environments. Figure 3 represents the MobileNet architecture.

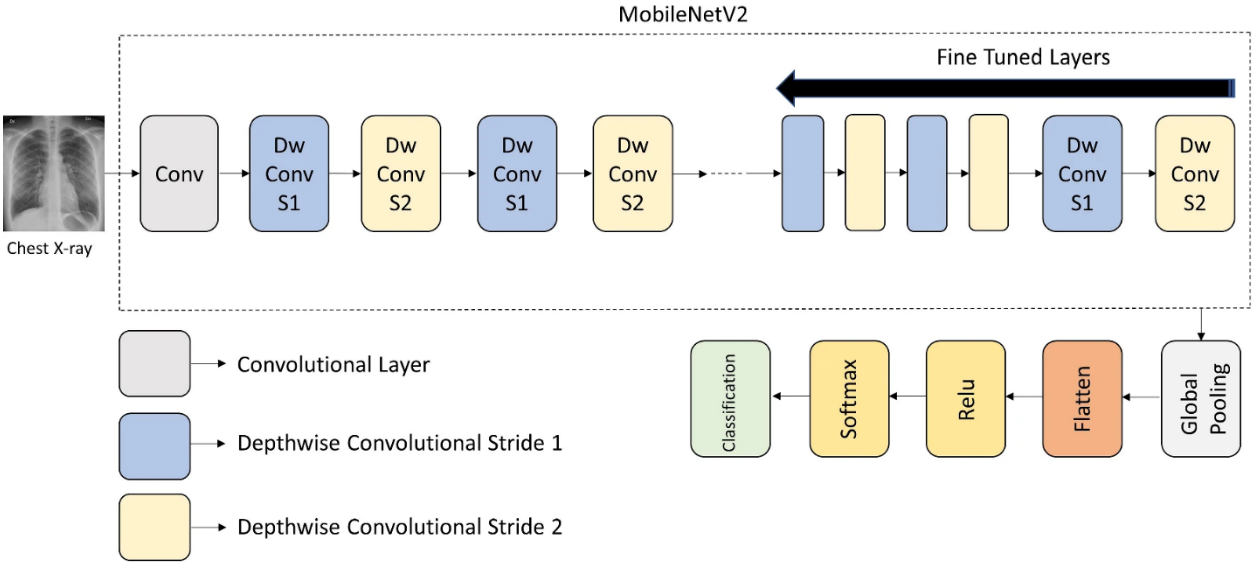

Figure3: Mobile Net architecture (Kaya, Y. 2023)

Xception architecture replaces traditional inception modules with depthwise separable convolutions, leading to superior performance with fewer parameters. Figure 4 represents the Xception structure.

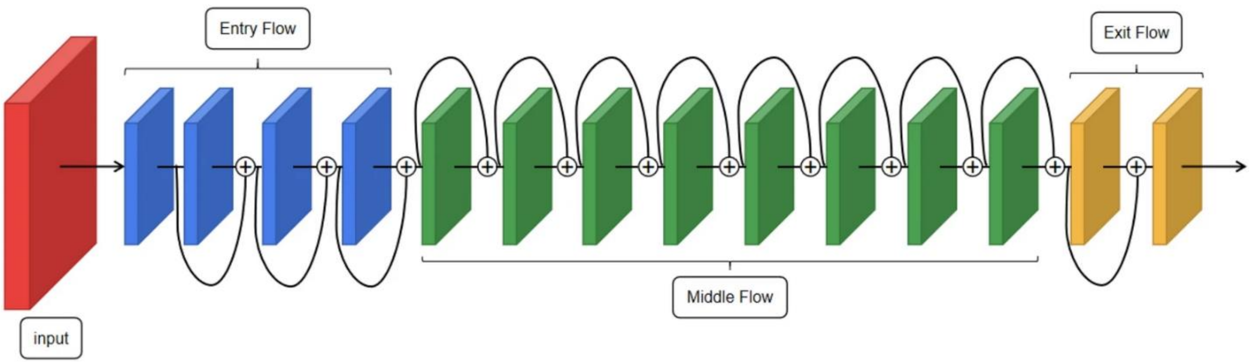

Figure4: Xception architecture (Liu, Y. 2022)

3.2. Datasets

We used a dataset (Bhuvaji, S. 2020) with 3264 MRI images, including 926 gliomas, 937 meningiomas, 901 pituitary tumors, and 500 non-tumor cases. Figure 1 showcases sample images from each category, highlighting inter- and intra-class diversity. The dataset was randomly split into 2612 training images and 652 test images for the experiments. Data are provided in Table 1.

Table 1. Brain tumor image dataset statistics

Class Name	Number of Images	Training	Testing
Glioma	926	743	183
Meningioma	937	736	201
No tumor	500	404	96
Pituitary	901	729	172
Total	3264	2612	652

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3.3. Preprocessing

Before training, several preprocessing steps were applied to the MRI images. First, all images were resized to 224x224 pixels to match the input requirements of the CNN models. Next, pixel values were normalized by scaling them to a range of 0 to 1. Additionally, data augmentation techniques, such as horizontal and vertical flips, rotations, and shifts, were employed to increase the diversity of the training set and enhance model robustness.

3.4. Training

The models were trained using several key parameters. We utilized the Adam optimizer with an initial learning rate of 0.001 and applied categorical cross-entropy as the loss function for multi-class classification. The batch size was set to 32, and the models were trained for 50 epochs. Additionally, based on monitoring the validation loss, early stopping with patience of 10 epochs was employed to prevent overfitting.

3.5. Evaluation Metrics

The performance of each model was evaluated using the following metrics:

- Accuracy: The proportion of correctly classified images.
- Sensitivity (Recall): The ability of the model to correctly identify positive cases.
- Specificity: The ability of the model to correctly identify negative cases.
- Precision: The proportion of true positive cases among the retrieved instances.
- F1-Score: The harmonic mean of precision and recall.

4. EXPERIMENTAL SETUP

The model was trained and evaluated on the same training, validation, and test sets to ensure a fair comparison. Hyperparameter tuning was performed to optimize model performance. To enhance the accuracy of brain tumor classification, we incorporated batch normalization and dense layers, which were crucial for regularization and enabling the model to identify complex patterns in medical images. Additionally, we meticulously adjusted hyperparameters, including the learning rate and batch size, to ensure optimal convergence and generalization of the model.

5. RESULTS

In the DenseNet model, For Glioma tumors, the model accurately classified 177 images as Glioma, achieving a 96.7% accuracy rate. It misclassified six Glioma images as Meningioma, and no Glioma images were incorrectly labeled as Pituitary or No Tumor. Regarding Meningioma tumors, the model correctly identified 191 images as Meningioma with a 97.1% accuracy. Misclassifications included two images as Glioma, one as Pituitary, and two as No Tumor. For Pituitary tumors, the model perfectly classified 172 images as Pituitary, resulting in 100% accuracy. It misclassified one image as Glioma, with no misclassifications as Meningioma or No Tumor. In the No Tumor category, the model correctly identified 93 images with a 97% accuracy rate. It misclassified two images as Glioma, one as Meningioma or Pituitary. Overall, the model achieved an approximate accuracy of 97.7%. The highest performance was observed for Pituitary tumors with a perfect accuracy of 100%, whereas Glioma showed the lowest accuracy at 96.7%.

In the MobileNet model, For Glioma tumors, the model accurately classified 175 images, achieving a 95.6% accuracy rate. It misclassified five Glioma images as Meningioma, two as Pituitary, and one as No Tumor. For Meningioma tumors, the model correctly identified 195 images with a 97.1% accuracy. Misclassifications included three images as Glioma, two as Pituitary, and one as No Tumor. For Pituitary tumors, the model accurately classified 169 images, resulting in a 98.2% accuracy. It misclassified three images as Glioma and one as Meningioma. In the No Tumor category, the model correctly classified 94 images, achieving a 97.9% accuracy rate. Misclassifications were two images as Glioma. Overall, the model achieved a 97.2% accuracy rate. The highest performance was observed for Pituitary tumors with an accuracy of 98.2%, while Glioma showed the lowest accuracy at 95.6%.

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In the Xception model, For Glioma tumors, the model accurately classified 176 images, achieving a 96.3% accuracy rate. It misclassified three Glioma images as Meningioma, two as Pituitary, and one as No Tumor. Regarding Meningioma tumors, the model correctly identified 189 images with a 94.1% accuracy. Misclassifications included six images as Glioma, four as Pituitary, and one as No Tumor. For Pituitary tumors, the model perfectly classified 172 images, resulting in 100% accuracy. There were no misclassifications of Pituitary images. In the No Tumor category, the model accurately classified 96 images, achieving a 100% accuracy rate with no misclassifications. Overall, the model achieved an approximate accuracy of 97.6%. The highest performance was for Pituitary and No Tumor with perfect accuracies of 100%, while Meningioma showed the lowest accuracy at 94.1%.

The results were analyzed to identify the strengths and weaknesses of each model. Performance metrics were compared in Table 2 and Figure 5, and statistical significance was assessed to determine the most effective model for brain tumor classification. The models' weights were initialized using trained weights derived from training on the dataset. Then, the classification layers were fine-tuned on the annotated brain tumor images from the dataset to tailor the learned features for the specific classification task.

Table 2. Results Analysis

	Accuracy	Sensitivity	Specificity	Precision	F1-Score
DenseNet	97.7%	96.2%	96.6%	97.1%	97.3%
MobileNet	97.2%	97.3%	97%	98.1%	96.6%
Xception	97.6%	97.9%	97.2%	98.5%	97.9%

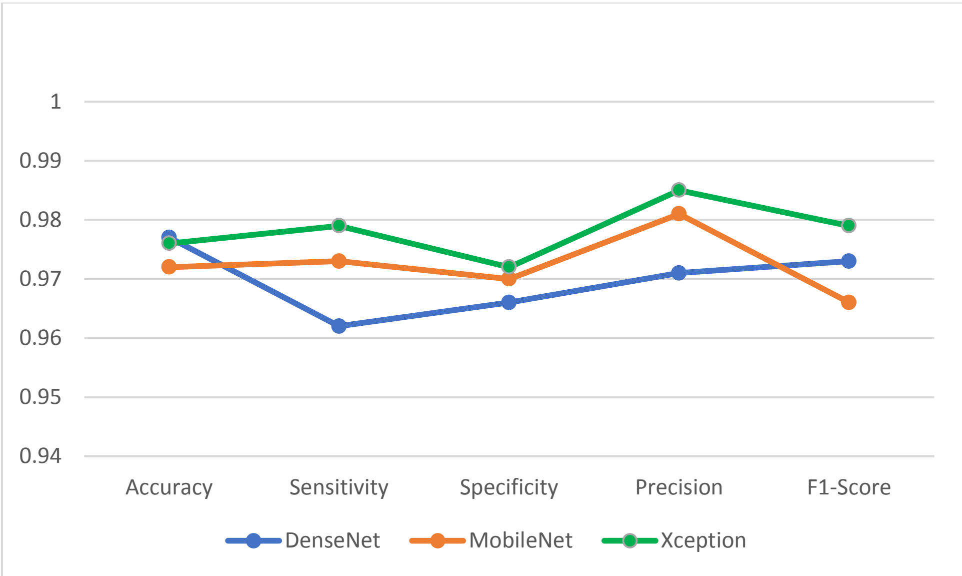

Figure5: Results Analysis

5.2 Discussion

The DenseNet, MobileNet, and Xception models show impressive capabilities in classifying brain tumors with overall accuracy rates of 97.7%, 97.2%, and 97.6%, respectively. DenseNet excelled in classifying Pituitary tumors with perfect accuracy of 100% but had some difficulty with Glioma tumors, which had the lowest accuracy at 96.7%. Similarly, MobileNet performed exceptionally well in classifying Meningioma tumors, achieving a 97.1% accuracy rate, yet struggled slightly with Glioma tumors, which showed an accuracy of 95.6%. The Xception model, on the other hand, perfectly classified Pituitary tumors and No Tumor cases with 100% accuracy, though its performance for Meningioma tumors was the lowest among the models at 94.1%.

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Comparatively, DenseNet and Xception models displayed near-perfect performance in most categories, particularly in classifying Pituitary tumors and No-Tumor cases, making them highly effective for clinical applications. MobileNet, while slightly behind in overall accuracy, demonstrated notable strengths in classifying Meningioma tumors. The analysis highlights the models' strengths and areas for improvement, particularly in distinguishing Glioma tumors. Future work should focus on enhancing the models' ability to differentiate between Glioma tumors and other types, as well as exploring more sophisticated techniques to improve overall classification accuracy. The results suggest that DenseNet and Xception models hold promising potential for accurate and reliable brain tumor classification, paving the way for their use in medical diagnostics and treatment planning but the Xception model has superior results.

6. CONCLUSION

This study assesses the classification performance of DenseNet, Xception, and MobileNet on the Brain Tumor Classification MRI scan dataset. The results indicate that all models, perform well, especially in identifying the “Pituitary” and “No-tumor” classes. Our results show that the Xception method excels over other architectures with an accuracy of 97.6%, making it highly effective in classifying abnormal and normal tumors from brain MRI images. By conducting a comprehensive comparison of models, applying rigorous fine-tuning, and utilizing effective regularization techniques, we endorse the Xception architecture as a highly accurate and generalizable model that is well-suited for clinical applications. Our findings emphasize the significance of selecting models tailored to specific clinical needs and computational limitations. Future studies should prioritize broadening and varying the dataset, as well as using data augmentation methods to tackle imbalances among the classes.

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