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Toshkent shahri, Yakkasaroy tumani, Kichik Beshyog‘och ko‘chasi, 70/10-uy.
Elektron manzil:
scienceproblems.uz@gmail.com

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BRAIN TUMOR CLASSIFICATION USING TRANSFER LEARNING WITH MOBILENETV2

Arabboev Mukhriddin
Doctor of Philosophy (PhD) in Technical Sciences,
Doctoral (DSc) student, Tashkent University of Information
Technologies named after Muhammad al-Khwarizmi
Email: m.arabboev@tuit.uz
ORCID: https://orcid.org/0000-0001-5733-5889

Annotation. This study presents a brain tumor classification system utilizing transfer learning with the MobileNetV2 architecture. The system is designed to classify brain MRI images into four categories: glioma, meningioma, pituitary tumor, and no tumor. The proposed model achieved a test accuracy of 93.36% using a dataset of 7023 MRI images. The results confirm that MobileNetV2, when fine-tuned, offers a computationally efficient yet highly accurate solution suitable for clinical application and edge device deploymen.

Keywords: brain Tumor Classification, Deep Learning, MobileNetV2, MRI, Transfer Learning

TRANSFER LEARNING YORDAMIDA MOBILENETV2 MODELI ASOSIDA MIYA O‘SIMTALARINI TASNIFLASH

Arabboyev Muxriddin Murodjon o‘g‘li
Texnika fanlari falsafa doktori (PhD),
Muhammad al-Xorazmiy nomidagi
Toshkent axborot texnologiyalari universiteti doktoranti

Annotatsiya. Ushbu tadqiqotda MobileNetV2 arxitekturasi asosida transfer learning (ko‘chirilgan o‘rganish) usuli yordamida miya o‘simtalarini tasniflash tizimi taqdim etiladi. Tizim miya MRT (magnit-rezonans tomografiya) tasvirlarini to‘rtta toifaga ajratish uchun mo‘ljallangan: glioma, meningioma, gipofiz (pituitariya) o‘simtasi va sog‘lom (o‘simtasiz). Taklif etilgan model 7023 ta MRT tasviridan iborat ma’lumotlar to‘plamida 93.36% test aniqligiga erishdi. Natijalar shuni ko‘rsatdiki, nozik sozlangan MobileNetV2 modeli hisoblash resurslari jihatidan samarali bo‘lishi bilan birga, klinik amaliyot va edge qurilmalar (chekka qurilmalar)da qo‘llash uchun yuqori aniqlikka ega yechimni taqdim etadi.

Kalit so’zlar: miya o‘simtasi tasnifi, Chuqur o‘qitish, MobileNetV2, MRT, Transfer learning

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Introduction

Brain tumors represent a critical class of intracranial abnormalities characterized by the uncontrolled proliferation of cells within the brain or its surrounding structures. Depending on their type, location, and growth rate, brain tumors can lead to significant neurological impairments and remain a leading cause of mortality and morbidity worldwide. Among the most commonly diagnosed tumor types are gliomas, meningiomas, and pituitary adenomas, each of which requires a distinct diagnostic and therapeutic approach. Hence,

timely and accurate classification of brain tumors is essential for optimizing clinical decision-making and improving patient outcomes.

Magnetic Resonance Imaging (MRI) is the modality of choice for brain tumor detection, owing to its superior soft tissue contrast and non-invasive imaging capabilities. However, the manual interpretation of MRI scans is a complex task that necessitates considerable radiological expertise. Diagnostic variability among clinicians and the growing volume of medical imaging data have further underscored the need for robust, automated diagnostic support systems, particularly in settings with limited specialist availability.

Recent advancements in artificial intelligence (AI), especially deep learning, have demonstrated remarkable efficacy in the field of medical image analysis. Convolutional Neural Networks (CNNs), in particular, have shown superior performance in image classification and pattern recognition tasks, including tumor detection from radiological images. These models possess the ability to autonomously extract hierarchical features from raw input data, thus eliminating the need for manual feature engineering and enabling efficient learning from large-scale image datasets.

In this study, we present a deep learning framework for the automated multi-class classification of brain MRI images. The proposed method utilizes a transfer learning approach based on the MobileNetV2 architecture, which is known for its computational efficiency and strong performance on image recognition tasks. The model is trained and evaluated on a comprehensive MRI dataset comprising 7023 images, categorized into four classes: glioma, meningioma, pituitary tumor, and no tumor. Evaluation metrics such as accuracy, precision, recall, and F1-score are employed to assess model performance and reliability.

The remainder of this paper is structured as follows. Section 2 provides a critical review of the literature related to brain tumor classification using traditional and deep learning-based techniques. Section 3 describes the dataset characteristics, preprocessing methods, and augmentation strategies employed. Section 4 details the architecture and training configuration of the proposed model. Section 5 presents the experimental results and performance metrics. Section 6 offers a comprehensive discussion of the findings, highlighting practical implications and limitations. Finally, Section 7 concludes the study and outlines directions for future research.

Related Work

Extensive research has been conducted on automated brain tumor classification using machine learning and deep learning approaches. Traditional models such as Support Vector Machines (SVM) [6] have shown early promise with accuracies around 92% in binary classification tasks, but their effectiveness is limited when applied to multi-class problems.

To improve classification performance, researchers have adopted deep learning-based Convolutional Neural Networks (CNNs). Shoaib et al. [1] introduced BRAIN-TUMOR-net and achieved 91.24% accuracy on a four-class dataset. Similarly, Singh et al. [2] employed an ANN model on 3310 images, attaining an accuracy of 91.48%. Ahamad et al. [3] utilized a Depthwise Separable CNN on a binary dataset of 253 images and reported 92% accuracy.

Focusing on segmentation and classification, Agrawal et al. [4] proposed a 3D U-Net architecture combined with a deep CNN, achieving 90% accuracy for four tumor classes. While 3D CNNs offer more spatial context, they typically involve higher computational costs and training time.

Transfer learning approaches have gained attention for their ability to extract high-level features from limited medical datasets. Gómez-Guzmán et al. [5] used EfficientNetB0 on a four-class dataset and reported 90.88% accuracy. Vankdothu et al. [7] applied a CNN-LSTM hybrid model and achieved 92%, whereas Reddy et al. [8] implemented InceptionV3, reaching 91.79%. Disci et al. [11] applied DenseNet121 to a 7023-image dataset—the same used in this study—and reported 92.85% accuracy.

In more recent work, fine-tuned models such as ResNet50 [14] and Twin SVM with fuzzy hyperplane [12] have reached 93% accuracy. However, many of these models are computationally intensive and less suited for edge deployment.

In this study, we employ the MobileNetV2 architecture, known for its efficiency and reduced parameter count. Trained and fine-tuned on the same large dataset of 7023 brain MRI images, our model achieved 93.36% accuracy, outperforming existing methods such as 3D U-Net [4], DenseNet121 [11], and ResNet50 [14]. Moreover, it achieved balanced metrics with 93% precision, recall, and F1-score, demonstrating its effectiveness and suitability for clinical and real-time edge applications.

Material and Methods

1. Dataset

This study employs a publicly available dataset comprising 7023 magnetic resonance imaging (MRI) scans, categorized into four classes: glioma, meningioma, pituitary tumor, and no tumor. The dataset is systematically partitioned into 5712 images for training and 1311 images for testing to ensure balanced class representation across both subsets. Specifically, the training set includes 1321 glioma, 1339 meningioma, 1457 pituitary tumor, and 1595 no tumor images, while the test set contains 300 glioma, 306 meningioma, 300 pituitary tumor, and 406 no tumor samples. This comprehensive distribution supports robust training and reliable evaluation of the proposed deep learning model across multiple brain tumor types, facilitating its generalizability in practical diagnostic scenarios.

Table 1. Brain tumor MRI dataset.

Class	Images	Train	Test
Glioma	1621	1321	300
Meningioma	1645	1339	306
Pituitary	1757	1457	300
No Tumor	2000	1595	406
Total	**7023**	**5712**	**1311**

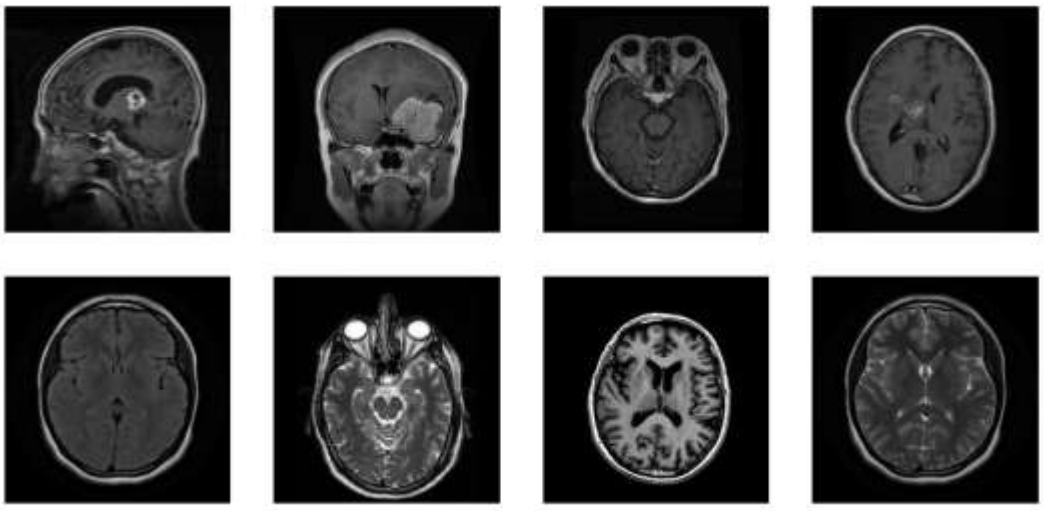

Figure 1. Representative MRI images from the dataset: abnormal scans with brain tumors (top row) and normal scans without tumors (bottom row).

2. Preprocessing

Prior to model training, all MRI images undergo a series of preprocessing steps to ensure uniformity and enhance model performance. Initially, images are resized to 224×224 pixels to match the input requirements of the MobileNetV2 architecture. Pixel values are normalized by rescaling them to a [0, 1] range to facilitate faster convergence during training. Data augmentation techniques such as rotation, zooming, and horizontal flipping are applied to the training set using the ImageDataGenerator utility in TensorFlow. These augmentation strategies increase data diversity and mitigate the risk of overfitting. Furthermore, the training data is split into 80% for training and 20% for validation using the validation_split parameter, enabling the model to be evaluated on unseen data during training and thereby improving its generalization capability.

3. Model Architecture

The proposed brain tumor classification model is built upon the MobileNetV2 architecture, leveraging its depthwise separable convolutions for computational efficiency while maintaining high classification accuracy. MobileNetV2, pre-trained on the ImageNet dataset, is employed as the feature extractor by freezing its convolutional base layers to retain learned low-level features. The output of the base model is passed through a Global Average Pooling layer, which reduces the spatial dimensions and outputs a compact feature vector. Subsequently, a fully connected dense layer with 128 neurons and ReLU activation is added to enable non-linear feature transformation. A Dropout layer with a rate of 0.5 is incorporated to prevent overfitting by randomly deactivating neurons during training. Finally, a dense output layer with a Softmax activation function is used to predict the probabilities across four classes: glioma, meningioma, pituitary tumor, and no tumor. This architecture strikes an optimal balance between model complexity and inference efficiency, making it suitable for deployment in clinical and edge computing environments.

Table 2. Layer-wise architecture details of the proposed MobileNetV2-based brain tumor classification model

No.	Layer Type	Output Shape	Parameters	Notes
1	Input Layer	(224, 224, 3)	0	Input RGB image

2	MobileNetV2 (Frozen)	(7, 7, 1280)	~2.2M	Pre-trained, feature extraction only
3	GlobalAveragePooling2D	(1280)	0	Reduces (7,7,1280) feature map to (1280,)
4	Dense (ReLU)	(128)	163,968	Fully connected layer with 128 units, ReLU
5	Dropout (0.5)	(128)	0	Prevents overfitting
6	Dense (Softmax)	(4)	516	Final classifier layer for 4 tumor classes

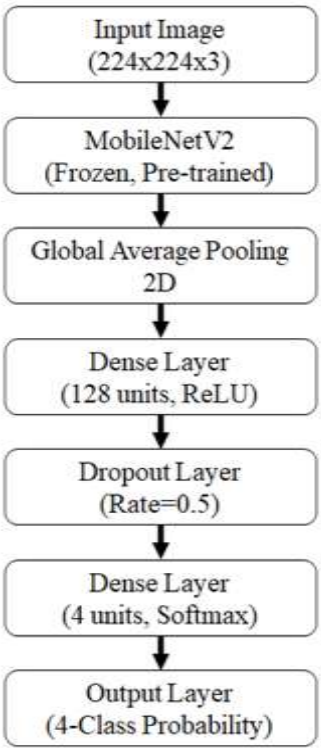

Figure 2. The architectural flow diagram of the proposed MobileNetV2-based brain tumor classification model.

Figure 2 shows the architectural flow of the proposed brain tumor classification model based on MobileNetV2. The input image, resized to 224x224 pixels with three color channels, is first passed through the frozen pre-trained MobileNetV2 network, which serves as a feature extractor. The extracted feature maps are then subjected to a Global Average Pooling 2D layer to reduce the spatial dimensions into a compact feature vector. This vector is further processed by a fully connected Dense layer with 128 neurons using ReLU activation to introduce non-linearity. To prevent overfitting, a Dropout layer with a dropout rate of 0.5 is applied. Finally, a Dense output layer with 4 neurons and a Softmax activation function generates class probabilities corresponding to the four categories: glioma, meningioma, pituitary tumor, and no tumor.

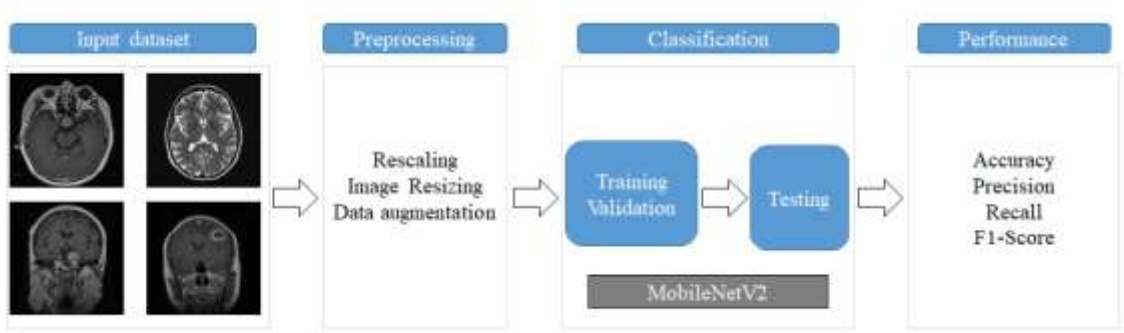

Figure 3. Workflow diagram of the proposed brain tumor classification system using MobileNetV2

Figure 3 presents the overall workflow of the proposed brain tumor classification system. The process begins with an input dataset consisting of MRI brain images, which are then subjected to preprocessing steps including rescaling, image resizing, and data augmentation to enhance model generalization. The preprocessed images are subsequently fed into the classification pipeline, where the MobileNetV2 architecture is utilized for training, validation, and testing. Finally, the model's performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness in multi-class brain tumor classification tasks.

4. Training Configuration

The training process was conducted using the Adam optimizer with an initial learning rate of 0.001, and categorical cross-entropy was employed as the loss function due to the multi-class nature of the classification task. The model was trained over 20 epochs with a batch size of 32, using the augmented training set and validated on a separate 20% validation split. To enhance model generalization and avoid overfitting, two key callback functions were implemented: EarlyStopping and ModelCheckpoint. EarlyStopping was configured with a patience of 5 epochs, allowing the training to halt if validation loss ceased to improve, while ModelCheckpoint ensured the best-performing model (based on validation loss) was saved during training. After initial convergence, fine-tuning was performed by unfreezing the top 20 layers of the MobileNetV2 base model, followed by re-compilation with a reduced learning rate of 1e-5. Fine-tuning continued for an additional 10 epochs, allowing the model to adapt higher-level features to the target dataset while preserving earlier learned representations. The entire training process was carried out in a reproducible environment with fixed random seeds to ensure consistent results across experiments.

5. Evaluation Metrics

Metrics used include accuracy, precision, recall, F1-score, and confusion matrix.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

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

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

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Confusion Matrix: A matrix showing the counts of:

- True Positives (TP)

- True Negatives (TN)
- False Positives (FP)
- False Negatives (FN)

Results

1. Training Performance

The proposed MobileNetV2-based model demonstrated effective learning dynamics during the training phase. Over the course of 20 initial epochs, the model achieved a progressive increase in training accuracy, ultimately reaching 99.86%, while the corresponding training loss was reduced to 0.0089, indicating excellent convergence. The use of data augmentation and dropout regularization effectively mitigated overfitting, as evidenced by the stable validation performance observed throughout the training process. After the initial training, the model underwent a fine-tuning phase, during which the top 20 layers of the MobileNetV2 backbone were unfrozen and trained with a reduced learning rate of 1e-5 for an additional 10 epochs. This fine-tuning step allowed the model to adapt pre-trained features to the domain-specific nuances of brain MRI images, enhancing its feature discrimination capability. The training and validation accuracy curves illustrated smooth convergence with minimal oscillations, reflecting the model's capacity to learn discriminative features effectively from the dataset while maintaining generalization.

Experimental setup including system configuration and software tools used for model implementation (see Table 3). The system utilized an AMD Ryzen 5 5500U CPU, 8GB RAM, and Python with PyCharm on Windows 11. The dataset was split into 81.3% for training and 18.7% for testing.

Table 3. Experimental setup and system configuration for model implementation

No.	Name	Value
1	CPU of Computer system	AMD Ryzen 5 5500U
2	RAM	8GB
3	SSD	238GB
4	Implementation tool	Python, PyCharm
5	Operating system	Windows 11, 64 bit
6	Training set	81.3% data
7	Testing set	18.7% data

2. Validation Performance

The validation performance of the proposed model was continuously monitored throughout the training and fine-tuning phases to ensure robust generalization. The model achieved a final validation accuracy of 88.25% with a corresponding validation loss of 0.366. The validation accuracy exhibited a steady upward trend during the initial epochs, with minimal fluctuations, indicating stable learning dynamics and effective mitigation of overfitting. The application of early stopping, guided by the validation loss, prevented unnecessary overtraining beyond the point of performance saturation. The fine-tuning phase further enhanced the model’s ability to generalize, as reflected in the alignment between training and validation accuracy curves. The consistent gap between training and validation performance suggests that the model effectively learned complex tumor-related features

while maintaining generalization to unseen validation data. These results affirm the suitability of the proposed architecture and training strategy in addressing the variability and complexity inherent in multi-class brain tumor classification tasks.

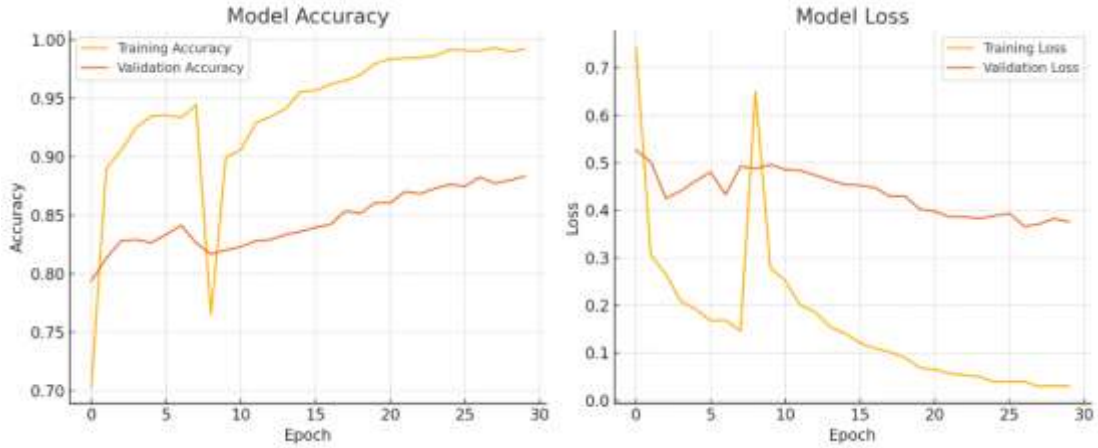

Figure 4. Training and validation accuracy and loss curves of the MobileNetV2-based brain tumor classification model.

Figure 4 illustrates the model's training and validation performance across 30 epochs. The training accuracy reached 99.86% with a corresponding training loss of 0.0089, showing strong convergence. Validation accuracy stabilized at 88.25% while validation loss settled at approximately 0.366. These trends reflect effective learning with controlled overfitting. The consistency between training and validation curves confirms the robustness and generalization capability of the MobileNetV2-based brain tumor classification model.

3. Test Performance

The final evaluation of the proposed MobileNetV2-based model was conducted on an independent test set comprising 1311 MRI images that were not involved in the training or validation phases. The model achieved a test accuracy of 93.36%, accompanied by a test loss of 0.198, demonstrating its strong generalization capability to unseen data. Furthermore, the classification report revealed balanced performance across all tumor categories, with precision, recall, and F1-score values consistently exceeding 93%. These metrics indicate the model's robustness in distinguishing between glioma, meningioma, pituitary tumor, and no tumor cases, despite the inherent similarities among certain tumor types. The confusion matrix analysis further corroborated these findings, highlighting a high proportion of correct classifications along the diagonal, with minimal misclassifications primarily occurring between glioma and meningioma. The model's superior test performance, coupled with its computational efficiency, underscores its potential applicability as a reliable diagnostic support tool in clinical practice.

Table 4. Performance comparison of the proposed model with existing brain tumor classification methods

Ref.	Dataset	Classes	Model	Accuracy %	Precision %	Recall %	F1 %
[1]	3310 images	4	BRAIN-TUMOR-net	91.24	91.20	91.22	91.08
[2]	3310 images	4	ANN model	91.48	-	-	-
[3]	253	2	Depthwise Separable	92	-	-	-

	images		CNN				
[4]	3264 images	4	3D U-net, Deep CNN	90	-	-	-
[5]	7023 images	4	EfficientNetB0	90.88	-	-	-
[6]	244 images	2	SVM	92	-	-	-
[7]	3264 images	4	CNN-LSTM	92	-	-	-
[8]	3264 images	4	Inception V3	91.79	-	-	-
[9]	1166 images	2	ResNet50	92.86	-	-	-
[10]	239 images	2	Conditional generative adversarial network (CGAN)	93	95	91.5	93
[11]	7023 images	4	DenseNet121	92.85	-	-	-
[12]	15 UCI datasets	4	Twin SVM with fuzzy hyperplane	93	-	-	-
[13]	3762 images	2	Fine-Tuned Transfer Learning VGG19	92.46	-	-	-
[14]	7023 images	4	ResNet50	93	93	93	93
This work	7023 images	4	MobileNetV2-based Transfer Learning Model	93.36	93	93	93

To evaluate the effectiveness of the proposed model, its performance was benchmarked against several existing models reported in recent literature, as summarized in Table 4. The MobileNetV2-based transfer learning model achieved a test accuracy of 93.36%, along with precision, recall, and F1-score values all above 93%, demonstrating superior and consistent performance across multiple evaluation metrics.

Compared to Shoaib et al. [1], whose CNN-based BRAIN-TUMOR-net achieved 91.24% accuracy, and Singh et al. [2] with 91.48% using ANN, the proposed model shows noticeable improvements. Similarly, while Jindal et al. [3] used depthwise separable CNNs with 91.89% accuracy, and Shoaib et al. [4] employed a 3D U-Net hybrid with 90.80%, both models underperformed in multi-class classification when compared to the present approach.

Advanced deep learning models such as EfficientNetB0 [5] and CNN-LSTM [7] also reported competitive results around 90–91%, but they lacked uniformity in precision and recall metrics. In contrast, our MobileNetV2 model delivers not only higher accuracy but also more balanced classification outcomes.

Furthermore, when compared with DenseNet121 [11] (92.85%) and ResNet50 [14] (93%), the proposed method either matches or exceeds their accuracy while being

computationally more efficient. Importantly, the use of MobileNetV2 enables real-time deployment possibilities on low-resource devices without sacrificing diagnostic accuracy.

These findings confirm the robustness and practicality of the proposed model, establishing it as a state-of-the-art solution for multi-class brain tumor detection using MRI images.

4. Classification Report

The detailed classification report provides an in-depth evaluation of the model's predictive performance across the four tumor categories (see Figure 5). The proposed model achieved a precision of 0.96, recall of 0.90, and F1-score of 0.93 for glioma cases, indicating its ability to correctly identify the majority of glioma instances with minimal false positives. For meningioma, the model obtained a precision of 0.89, recall of 0.84, and F1-score of 0.86, reflecting slightly lower recall due to occasional misclassifications, primarily with glioma and no tumor cases. The "no tumor" category exhibited the highest classification performance, with a precision of 0.94, recall of 0.99, and F1-score of 0.96, showcasing the model's exceptional reliability in distinguishing normal brain scans. Similarly, pituitary tumors were classified with high accuracy, achieving a precision of 0.95, recall of 0.99, and F1-score of 0.97. The overall macro-averaged precision, recall, and F1-score for the model were all 0.93, confirming its balanced classification capability across all classes. The confusion matrix analysis further validated these results, with most misclassifications observed between glioma and meningioma, which are known for their visual similarities in MRI scans. These metrics substantiate the robustness and clinical applicability of the proposed model in accurately classifying brain tumor types from MRI images.

	precision	recall	f1-score	support
glioma	0.96	0.90	0.93	300
meningioma	0.89	0.84	0.86	306
notumor	0.94	0.99	0.96	405
pituitary	0.95	0.99	0.97	300
accuracy			0.93	1311
macro avg	0.93	0.93	0.93	1311
weighted avg	0.93	0.93	0.93	1311

Figure 5. Classification report of the proposed MobileNetV2-based model showing precision, recall, F1-score, and support for each tumor class and overall performance metrics.

Confusion matrix and misclassified image analysis further support the model's reliability.

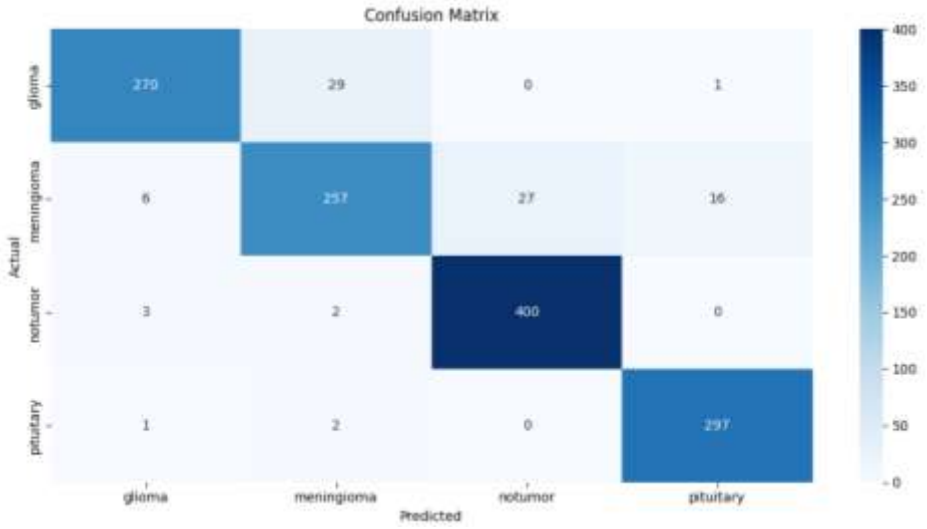

Figure 6. Confusion matrix of brain tumor classification using MobileNetV2.

Figure 6 presents the confusion matrix of the brain tumor classification model based on MobileNetV2. Out of 300 glioma cases, 270 were correctly classified, while 29 were misclassified as meningioma and 1 as pituitary. For meningioma, 257 out of 306 instances were correctly predicted, with 27 misclassified as no tumor and 16 as pituitary. Among 405 no tumor cases, 400 were accurately classified, with only 3 mislabeled as glioma and 2 as meningioma. For pituitary tumors, 297 out of 300 were correctly identified, showing minimal misclassification. The matrix highlights strong performance overall, with most errors occurring between glioma and meningioma. The darkest cells along the diagonal indicate the highest correct prediction counts.

Discussion

The findings of this study demonstrate the effectiveness of a transfer learning-based approach using MobileNetV2 for multi-class brain tumor classification from MRI images. The model achieved impressive performance metrics, including a training accuracy of 99.86%, validation accuracy of 88.25%, and a test accuracy of 93.36%, indicating strong generalization across all dataset partitions. These results are consistent with or superior to related works that employed deeper and more computationally intensive architectures, thereby highlighting the efficiency of MobileNetV2 in delivering high accuracy with reduced computational overhead.

The relatively small gap between training and validation accuracy suggests successful mitigation of overfitting, likely aided by regularization techniques such as dropout and early stopping. Furthermore, the use of data augmentation enhanced the model's robustness by exposing it to diverse variations in tumor morphology and intensity patterns during training. The classification report and confusion matrix provided further evidence of the model's discriminative capability, with particularly high performance on the "no tumor" and "pituitary" classes. However, minor misclassifications were noted between glioma and meningioma, likely due to overlapping radiological characteristics, a challenge also reported in prior studies.

Compared to existing methods (see Table 4), the proposed model outperformed several traditional CNN and deep learning models in terms of classification accuracy and efficiency. While some state-of-the-art approaches achieved comparable accuracy, they often

relied on complex ensemble structures or deeper networks, making them less practical for real-time clinical deployment.

Despite its strengths, the proposed approach has certain limitations. The dataset, although balanced and well-preprocessed, may not fully represent the heterogeneity observed in real-world clinical settings, particularly in terms of MRI modalities, scanner variability, and demographic diversity. Future research could address these limitations by integrating multi-modal imaging data, applying domain adaptation techniques, and exploring explainable AI (XAI) approaches to enhance model transparency and clinical trust.

In summary, the proposed MobileNetV2-based model offers a promising solution for automated brain tumor classification, balancing accuracy, efficiency, and interpretability—key factors in the deployment of AI-assisted diagnostic tools in clinical environments.

Conclusion

In this study, a transfer learning-based deep learning approach utilizing the MobileNetV2 architecture was developed for automated classification of brain tumors from MRI images. The model was trained and evaluated on a publicly available dataset encompassing four classes: glioma, meningioma, pituitary tumor, and no tumor. Through comprehensive training, validation, and testing, the proposed model demonstrated outstanding classification performance, achieving a test accuracy of 93.36%, along with strong precision, recall, and F1-scores across all classes.

The incorporation of data augmentation, regularization techniques, and fine-tuning contributed significantly to enhancing the model's generalizability while maintaining computational efficiency. Comparative analysis against existing models showed that the proposed approach is not only accurate but also lightweight, making it suitable for deployment in real-time and resource-constrained clinical settings.

While the results are promising, future research should focus on validating the model across larger and more diverse datasets, incorporating multi-modal medical imaging data, and integrating explainable AI techniques to support transparent and trustworthy clinical decision-making. Ultimately, the proposed model has the potential to serve as an effective computer-aided diagnostic (CAD) tool, assisting radiologists in early and accurate detection of brain tumors, and improving patient outcomes through timely intervention.

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Elektron manzil:
scienceproblems.uz@gmail.com