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RESEARCH ARTICLE

An Intelligent and Lightweight Approach Based on MobilenetV2 Architecture for Identifying Brain Tumors

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ABSTRACT
Integration of machine learning approaches has the potential to alleviate human error and reduce the time required to diagnose brain tumors by assisting radiologists. The main focus of the existing studies is on developing a model that is as accurate as possible to perform such a task. On the other hand, a model's computational cost and image processing speed are not extensively examined. However, they are significant parameters for the model deployment in real-time. This study aims to close the gap by introducing MobileNetV2-0.5 as a lightweight, fast, and effective approach for identifying brain tumors using real-time Magnetic Resonance Imaging (MRI) images. The results indicated that the proposed approach successfully identified the tumors by 98.78% and detected the non-tumor cases by 99.75%. The computational cost and the processing speed have improved by around 50% compared to the original MobileNetV2 architecture. A similar improvement has also been observed when comparing the proposed approach with the models existing in the literature. Based on the results of the analysis, it is concluded that the proposed MobileNetV2-0.5 has the potential to identify brain tumors in real-time by deploying the model through embedded devices.

Keywords: Brain tumor detection, MobileNetV2, Deep Learning, Machine Learning

1. Introduction

Accurately detecting and identifying brain tumors at their earliest stage is important in medicine for effectively treating patients. As one of the standard techniques, Magnetic Resonance Imaging (MRI) is used for that purpose. Despite its effectiveness, it is a time-consuming process where the evaluation may vary depending on the expert, resulting in inconsistent diagnoses. Based on this situation, a validation procedure may help the experts to detect and identify brain tumors precisely.

Deep learning approaches show promising outcomes in assisting radiologists in the assessment of brain tumors [1-5]. Empowering such approaches with MRI images has the potential to establish a solid ground in finding brain tumors and distinguishing the brain tumor types, assisting practitioners in proceeding with the correct treatment. Based on this motivation, researchers developed various intelligent models to detect and identify brain tumors through machine learning techniques. Among these approaches, the majority are based on deep learning approaches where MRI images have been employed as input to detect [6-9] and identify [10-12] brain tumors effectively. Some of those works have been summarized as follows.

Sharmily et al. employed numerous deep learning approaches, including Convolutional Neural Networks (CNN), ResNet, UNet, Capsule Networks, and Transfer Learning, to detect and identify brain tumors [13]. They criticized the approaches considered for this specific topic based on their performance, complexity, interpretability, and execution time. Sadad et al. employed the UNet-ResNet50 backbone for segmentation tasks in detecting brain tumors [14]. They also considered other deep-learning approaches for comparison in tumor classification tasks. They achieved a 0.9054 intersection over the union (IoU) level and obtained a 99.60% accuracy for the NASNet model. Abdusalomov et al. proposed a fine-tuned version of YOLOv7 for brain tumor detection [15]. They obtained a 99.50% accuracy and claimed that the proposed approach can detect small tumors. Arı and Hanbay employed extreme learning machine local receptive fields (ELM-LRF) for tumor classification [16]. They considered only the cranial MRI images that had a mass. They obtained an accuracy of 97.18% using their proposed approach with these images. Saeedi et al. proposed a 2D CNN and a convolutional auto-encoder network to detect

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brain tumors using MRI images [17]. They compared their proposed approaches with different machine learning techniques, including Multilayer Perceptron (MLP), Random Forest (RF), Support Vector Machines (SVM), Linear Regression (LR), Stochastic Gradient Descent (SGD), and k-Nearest Neighbors (kNN). They concluded that 2D CNN and a convolutional autoencoder network demonstrated a good performance in detecting brain tumors with average accuracies of 96.47% and 95.63%, respectively. Balamurugan et al. used ResNet101 with an attention mechanism called Channel-wise Attention Module (CWAM) for brain tumor classification [18]. They compared the proposed approach with the deep learning techniques in the literature and the base ResNet101, including its combinations with different attention mechanisms. They achieved a 99.83% accuracy in detecting brain tumors.

As inferred from the studies above, numerous approaches have achieved high accuracy in detecting brain tumors. However, just like every intelligent model, such accuracy comes with a computational cost, which is critical in determining the hardware specification where the model will be executed. Furthermore, it designates the time required to process the images and produce the prediction.

The existing studies mostly focused on the success of a developed model, specific to accuracy, rather than considering the computational cost. Therefore, a developed model's complexity, size, and hardware requirements have been generally overlooked. This study aims to close the gap by proposing a lightweight approach using pruning procedures based on the ImageNet-pretrained MobileNetV2 architecture. The pruning strategy has been set to improve the effectiveness of MobileNetV2 in terms of accuracy and computational cost by eliminating the inverted residuals starting from the deepest blocks, as they contain higher output channels, which significantly increases the computational cost and may be redundant. The fundamental motivation of this study is to propose an accurate and lightweight approach for brain tumor identification that can be implemented in primarily rural or under-sourced clinics with limited internet and hardware access. The contributions of this study can be summarized as follows.

i. Introducing a pruned version of MobileNetV2 to identify brain tumors using MRI images for the first time, to provide a cost-effective, accurate model operable in low-end devices used in rural clinics where high-end hardware is unavailable.

ii. Providing discussions related to the computational cost and the processing speed of the pruned MobileNetV2 architecture in identifying brain tumors for the first time.

iii. Comparing the performance of the proposed approach with other pruned versions and the original version of MobileNetV2, as well as existing techniques in the literature, to identify brain tumors.

iv. Demonstrating the generalizability and robustness of the proposed approach using a composed brain MRI dataset collected from three different sources.

The remainder of this study is as follows. Section 2 briefly introduces the developed pruned MobileNetV2 architecture. Section 3 provides the details related to the dataset and the analysis conducted within the scope of this study. Finally, Section 4 concludes the outcomes of this work by addressing the key outcomes and future work

2. Methodology: Pruned MobileNetV2 Architecture

MobileNetV2 is developed to achieve a lightweight and accurate architecture suitable for implementation into embedded and mobile devices due to its lower computational cost, compatibility with ARM CPUs and older mobile GPUs, and low-cost trade-off between speed and accuracy [19]. Compared to MobileNetV1, MobileNetV2 introduces Inverted Residuals, which follow a narrow input–narrow output (projection) strategy where the computations occur in the expanded depth-wise convolution layer, whose output is narrowed again to reduce dimensions. By only keeping the narrow layers, the architecture becomes more efficient regarding computational cost and memory usage compared to the MobileNetV1 architecture. Furthermore, it brings Linear Bottlenecks that keep the information by preventing the output from being processed through the ReLU activation function, which can cause information loss [19]. A MobileNetV2 architecture comprises depthwise separable convolutions, inverted residual blocks, convolutional layers, and a classification section where a global average pooling layer and a fully connected layer exist. The depthwise separable convolution layer reduces the computational cost significantly while keeping the spatial information. The inverted residual blocks first expand the dimension of the channels of an image, then extract the spatial features, and finally, reduce the dimension of the channels back to the original dimension. If the output's dimension equals the input's dimension, the residual connection phase occurs where the input is added to the output, enabling the information flow for further processes. In a full architecture, there are 18 inverted residual blocks where the convolutional layer of the final block has 1280 channels. Following this inverted residual block, the classification is made through a dense layer, a global average pooling layer, and a softmax layer. Although the fundamental goal of developing the MobileNetV2 architecture is to reduce the computational cost with a minimum trade-off in accuracy, the architecture can be organized by correctly pruning the computationally high-cost layers to make the model lightweight than its original version. In this study, a pruned version of MobileNetV2, called MobileNetV2-0.5, is introduced where the final eight inverted residual blocks and the final convolution layer (Conv2D with 320 input channels and expansion to 1280) have been pruned. Moreover, the classifier part has been reduced to a lightweight layer (4 from 64). The illustration of the proposed approach is depicted in Figure 1. The main reason for pruning the final blocks is the number of channels at the highest level in those blocks. Therefore, more pruning from the final blocks results in fewer resources for the model.

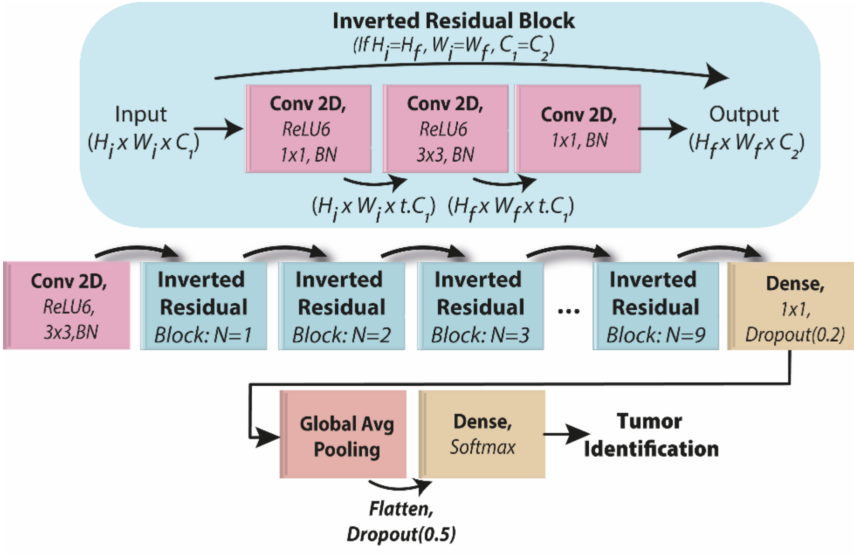

Figure 1. The illustration of the proposed approach.

3. Experimental Analysis

3.1. Dataset

All analyses have been conducted using a publicly available brain tumor MRI dataset where 7023 images of human brain MRI exist [20]. Those visuals are classified into four classes: glioma, meningioma, no tumor, and pituitary, with the distribution rates of 23.1%, 23.4%, 28.5%, and 25.0%, respectively. The dataset is denoted as the combination of three datasets: the figshare brain tumor dataset, the SARTAJ brain tumor dataset, and the Br35H brain tumor dataset. All figures have a size of 512x512 and a bit depth of 24. An illustration of the MRI images that existed in the dataset is shown in Figure 2. Before initiating the training, four data augmentation techniques (Random Vertical Flip, Random Horizontal Flip, Random Rotation, and Color Jitter) are employed to improve the robustness and the generalizability of the proposed approach.

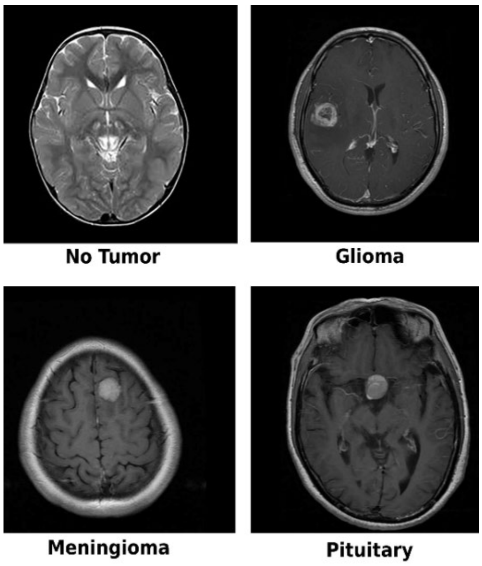

Figure 2. An Illustration of the Brain Tumor Conditions Existed in the Dataset [20]

3.1. Results and Discussions

Compared to MobileNetV2, MobileNetV3, and EfficientNet may perform better in accuracy. However, they require more computational tasks and usually demand newer, more expensive, and powerful devices [19, 21, 22]. Specific to this study, the original MobileNetV2, MobileNetV3, and EfficientNet-B0 accuracy is obtained as 98.40%, 97.41%, and 99.38%, respectively. Although EfficientNet-B0 is superior, fine-tuning does not result in significant improvements in either the accuracy (dropped by 0.1%) or the computational cost (346M from 390M FLOPs) as reported in Hou et al. [23]. On the other hand, if done meticulously, MobileNetV2 has room for improvement through pruning. Depending on the case and pruning strategy, it may significantly improve accuracy and computational efficiency [23]. Based on the reasons given above, MobileNetV2 is considered and optimized to achieve high performance and low computational cost in brain tumor identification.

The proposed MobileNetv2-0.5 has been evaluated using accuracy, precision, recall, and F1 score regarding the model's success in identifying the tumor types, including no tumor condition. The model assessment has also been conducted for speed through frames per second (FPS), computational load by floating point operations (FLOPS), and the number of parameters. Before proceeding, the images are resized to 256 x 256 to lower the computational costs. All analyses were performed on a computer with a mid-range six-core processor running at 2.70 GHz, 32 GB of RAM, and a GPU with 4 GB of memory.

A hyperparameter analysis has been conducted to obtain the most optimized model. For this purpose, the image size and the pretraining condition have been considered. Table 1 presents the analysis results based on the hyperparameters considered. After data augmentation, the performance of the proposed approach increased by 2.55% in accuracy.

Table 1. Hyperparameter Analysis Results of the Proposed Approach

Image-Size	Pre-trained	Accuracy	Precision	Recall	F1-Score
32x32	None	86.35%	0.864	0.864	0.864
32x32	ImageNet	88.86%	0.888	0.888	0.888
64x64	None	89.96%	0.890	0.870	0.860
64x64	ImageNet	92.20%	0.922	0.922	0.922
128x128	None	91.38%	0.914	0.914	0.914
128x128	ImageNet	92.30%	0.923	0.923	0.923
256x256	None	93.65%	0.937	0.937	0.937
256x256	ImageNet	96.23%	0.962	0.962	0.962

Figure 3 shows the historical plots for the training and validation loss values. Table 1 presents the ablation study results of the proposed approach with other MobileNetV2 architectures. MobileNetV2 is the original architecture without pruning, and MobileNetV2-0.75 is another pruned version of the original model where the last six inverted residuals are pruned.

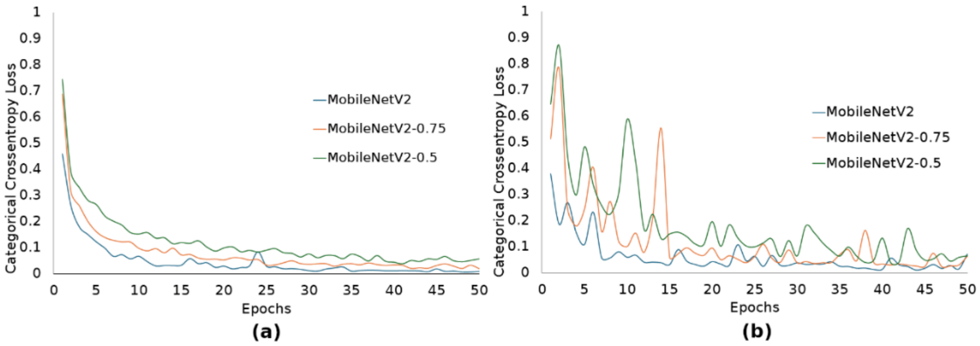

Figure 3. The history plot of the MobileNetV2 architectures for (a) training and (b) validation set

Table 2. Ablation Study Results

Model	Accuracy	Precision	Recall	F1 Score	FPS	FLOPS	No. Params
MobileNetV2	98.40%	0.984	0.984	0.984	418.51	1.67 G	3.51 M
MobileNetV2-0.75	98.40%	0.984	0.984	0.984	534.80	1.07 G	1.71 M
MobileNetV2-0.5	98.78%	0.988	0.988	0.988	739.98	205.06 M	1.47 M

As seen in Table 2, MobileNetV2 and MobileNetV2-0.75 have higher computational cost and demonstrated lower performance compared to the proposed MobileNetV2-0.5. In such cases, it is important to determine the trade-off between speed, computational cost, and accuracy, constituting a balance among them. In critical decisions where the cost of the decision has the utmost importance, accuracy must be put above other metrics. Brain tumor identification can be considered as one of those cases since a patient's life may depend on a decision. Therefore, among the MobileNetV2 architectures provided above, MobileNetV2-0.5 constitutes a good balance between accuracy, speed, and computational load. It is slightly more accurate, approximately 50% faster, and requires 88% lower computational cost than MobileNetV2. Furthermore, the number of parameters is less than 50% compared to the original architecture. MobileNetV2-0.75 has also provided promising results as its accuracy has not changed, while it has processed the images faster and developed a model with lower computational cost than MobileNetV2. The goal of the pruning procedure for this study is to alleviate the computational load by eliminating the redundant layers. According to the results reported in Table 2, the accuracy of the original MobileNetV2 model is slightly increased for the proposed approach. This suggests that a smaller model may generalize better and be less prone to overfitting for different tasks. The models with deeper layers may sometimes overestimate specific patterns, while more shallow approaches may learn robust features, improving performance. The confusion matrix and the ROC-AUC curve of the proposed approach are shown in Figures 4 and 5 to understand brain condition-based performance.

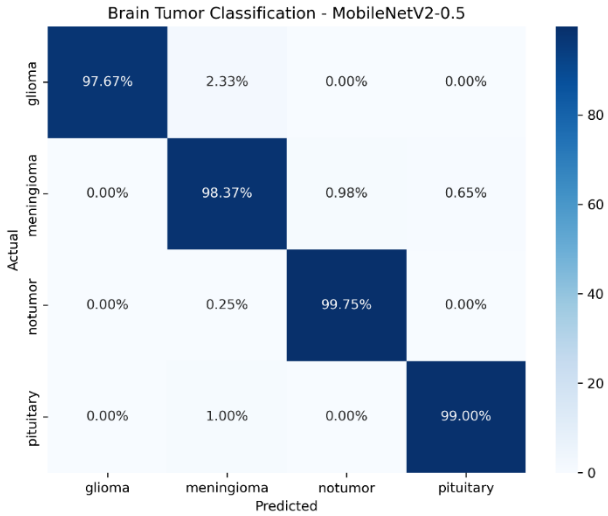

Figure 4. The history plot of the MobileNetV2 architectures for (a) training and (b) validation set

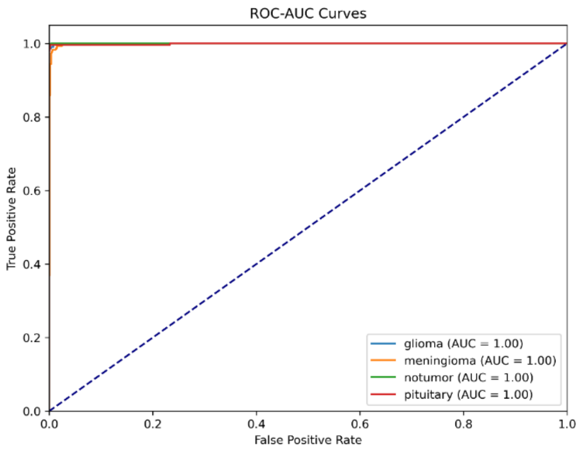

Figure 5. The ROC-AUC curves for each brain tumor condition

As seen in Figure 4, the proposed algorithm successfully and accurately identifies all brain conditions. The critical condition distinguishes the no-tumor condition from the tumor condition, as the first step is determining whether a tumor exists. The proposed model has performed almost perfectly in distinguishing the no tumor case from glioma, meningioma, and pituitary. According to the confusion matrix in Figure 3, if the model comes up with a decision in favor of no tumor condition, it is 99.75% correct. Meanwhile, the lowest accuracy was obtained for the glioma tumor, with an identification accuracy of 97.67%. The ROC-AUC curves in Figure 4 support the outcomes in Table 1 and Figure 3, indicating a decent performance in distinguishing all conditions. To evaluate the proposed approach with the models existing in the literature, a comparison considering all the metrics used in this study has been made, and the results are presented in Table 3. Those that did not report any metrics are indicated with "-" within the table.

Table 3. Comparison of the proposed approach with the existing models in the literature

Model	Accuracy	Precision	Recall	F1 Score	FPS	FLOPS	No Params.	Size (MB)
Inception V3 [24]	99.47%	0.994	0.994	0.994	-	-	-	-
GoogleNet [24]	98.25%	0.981	0.981	0.981	-	-	-	-
EfficientNet-B0 [24]	99.54%	0.995	0.995	0.995	-	-	-	-
CNN [12]	95.48%	0.953	0.962	-	-	-	-	-
CNN + Spare Represent [12]	98.41%	0.984	0.974	-	-	-	-	-
VGG16 [25]	98.60%	0.985	0.988	0.991	-	-	17M	56.5
DenseNet/3DCNN [26]	92.10%	0.920	0.926	0.916	-	-	-	-
ResNet50 [27]	97.60%	0.976	0.982	0.979	-	-	36.4M	93.8
Fine-Tuned MobileNetV2 [11]	99.00%	0.996	0.997	0.991	-	-	4.8M	17.64
Proposed Approach	98.78%	0.988	0.988	0.988	739.98	205.06M	1.47M	5.82

Table 3 shows a small difference between the proposed approach and the EfficientNet-B0 model, with the highest accuracy of 99.54%. However, the negligibly higher approaches (<1%) than the proposed approach demand more computational resources. Although, the model sizes are not provided in the corresponding study [24] for EfficientNet-B0 and Inception V3 that have higher accuracy values than the proposed approach, it is reported in the studies that they are introduced [21, 28]as around 390M for EfficientNet-B0 and 5700M for InceptionV3 for image sizes of 224x224 and 299x299, respectively. Based on this comparison, it can be stated that the proposed approach is a lightweight, fast, and effective approach that can be implemented and executed in an embedded device (e.g., Raspberry Pi or NVIDIA Jetson Nano).

3. Conclusions

This study proposed an improved and pruned version of the MobileNetV2 architecture, denoted as MobileNetV2-0.5, for effectively identifying brain tumors using MRI images. The proposed approach closes the gap related to the constitution of the balance between computational cost, speed, and accuracy, which have not been sufficiently investigated. The proposed approach has constituted such a balance by trading less than 1% accuracy for 85% less computational cost than the most accurate model (EfficientNetB0) reported in the literature. Additionally, the performance of the original MobileNetV2 model has been slightly improved, while around a 50% improvement in FPS and FLOPS has been achieved. Due to its superior aspects, MobileNetV2-0.5 can be considered in real-time by implementing the model in embedded devices. Furthermore, the analysis results indicate that it could be utilized for other purposes of MRI image-related disease identification. Therefore, this study's future work may incorporate assessing the proposed approach for different diseases and tuning the model to close the small accuracy gap.

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