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Enhancing Reliability in Deep Learning Diagnosis of Brain Tumors Using Grad-CAM

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Abstract

While deep learning models in medical imaging have gained popularity as a means to enhance patient outcomes and diagnostic accuracy recently, one of their main issues is interpretability, which is essential to understanding and debugging the model. Explainable Artificial Intelligence (XAI) is a recent rising research direction that aims to explain this black box part of the deep learning models. For quick identification, clinical evaluations and imaging methods such as Magnetic Resonance Imaging (MRI) scans, are frequently utilized; nevertheless, manual analysis has challenges such as subjectivity and delays. On the other hand, AI-based models convey a more rapid and reliable approach to classifying and detecting brain tumors. In this work, a transparent and explainable framework of pre-trained Convolutional Neural Network (CNN) models combined with Gradient Weighted Class Activation Mapping (Grad-CAM) for the classification of brain MRI images is presented. The effectiveness of ResNet50, DenseNet121, MobileNetV2 and ConvNeXtTiny architectures is compared. A test accuracy of 100% and precision-recall scores above 99.90% is obtained, highlighting the model's effectiveness in identifying whether a tumor is present. The results illustrate how the models have enhanced localization skills by visualizing the regions of focus in the predictions through the application of the Grad-CAM method. This blend of interpretability offers a promising step toward creating more reliable and understandable tools for diagnosing brain tumors.

Keywords

Tumor Detection,
Grad-CAM,
Deep Learning

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Derin Öğrenme ile Beyin Tümörlerinin Teşhisinde Grad-CAM Kullanarak Güvenilirliğin Artırılması

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Özet

Tıbbi görüntülemede derin öğrenme modelleri, hasta sonuçlarını ve tanı doğruluğunu iyileştirmenin bir yolu olarak son zamanlarda popülerlik kazanmış olsa da, bu modellerin temel sorunlarından biri, modeli anlamak ve hata ayıklamak için gerekli olan yorumlanabilirliktir. Açıklanabilir Yapay Zeka, derin öğrenme modellerinin bu kara kutu kısmını açıklamayı amaçlayan, son zamanlarda yükselen bir araştırma yönüdür. Hızlı tanımlama için, manyetik rezonans görüntüleme taramaları gibi klinik değerlendirmeler ve görüntüleme yöntemleri sıklıkla kullanılır; ancak manuel analiz, öznellik ve gecikmeler gibi zorluklar içerir. Öte yandan, yapay zeka tabanlı modeller, beyin tümörlerini sınıflandırma ve tespit etme konusunda daha hızlı ve güvenilir bir yaklaşım sunar. Bu çalışmada, beyin MRI görüntülerinin sınıflandırılması için önceden eğitilmiş Konvolüsyonel Sinir Ağı modellerinin Gradyen Ağırlıklı Sınıf Aktivasyon Haritalama (Grad-CAM) ile birleştirildiği şeffaf ve açıklanabilir bir çerçeve sunulmaktadır. ResNet50, DenseNet121, MobileNetV2 ve ConvNeXtTiny mimarilerinin etkinliğini karşılaştırılarak %100 test doğruluğu ve %99,90'ın üzerinde hassasiyet-geri çağırma puanları elde edilmiştir. Bu da modelin tümörün varlığını tespit etmedeki etkinliğini vurgulamaktadır. Sonuçlar, Grad-CAM yönteminin uygulanmasıyla tahminlerde odaklanılan bölgeleri görselleştirerek modellerin lokalizasyon becerilerini nasıl geliştirdiğini göstermektedir. Bu yorumlanabilirlik özelliği, beyin tümörlerini teşhis etmek için daha güvenilir ve anlaşılır araçlar oluşturma yolunda umut verici bir adımdır.

Anahtar kelimeler

Tümör Teşhisi,
Grad-CAM,
Derin Öğrenme

1. INTRODUCTION

Medical imaging has become a key part of healthcare today, enabling clinic heroes to diagnose and treat various illnesses more precisely than in the past. Among these illnesses, the detection and classification of brain tumors are of paramount importance due to their potentially life-threatening nature. Tumors can be defined as either malignant or benign. A brain tumor is the most common type of brain disease. It is an uncontrolled proliferation of brain cells [1]. These tumors can put pressure on various areas of the brain, affecting its functioning in a dangerous manner [2]. Benign tumors grow slowly and remain localized, while malignant tumors are very aggressive and move to different parts of the body. Brain tumors are classified I-IV by the World Health Organization (WHO). Categories I and II tumors are considered to develop slowly, while categories III and IV tumors are usually malignant and possess an unfavorable prognosis [3]. When it comes to identifying brain tumors, MRI is considered to be the most commonly used imaging technique. It is a non-invasive soft tissue contrast imaging technology that provides vital information about the location, size, and shape of brain tumors without exposing patients to excessive amounts of radiation [4]. The diagnosis of a brain tumor is a laborious process that mostly relies on the radiology specialist's expertise. The volume of data that has to be analyzed has increased dramatically due to the increased patient population density, making traditional procedures costly and inaccurate. Significant differences in brain tumor intensity, shape, and size within the same tumor type, as well as comparable symptoms of other disease types, are linked to the challenges. A brain tumor's misdiagnosis can have serious consequences and lower the chance of survival for the patient.

Automated image processing technologies are gaining popularity because they help overcome the challenges associated with manual diagnosis and similar applications. In simpler terms, these technologies are becoming more common as a way to make diagnosing illnesses and other tasks easier and more efficient than doing them by hand [5-7]. Recently, a number of computer-aided diagnostic (CAD) systems have been developed to automatically diagnose brain tumors [8]. Developments in deep learning and AI have completely changed the area of medical image analysis by providing powerful tools for automated prediction and diagnosis [1]. One of the prominent architectures that have garnered significant attention in the realm of image classification is CNN. While CNNs have long been the go-to choice for various domains, including classification of natural images and medical imaging. Understanding what CNN models see in brain tumor image classification holds significant implications for clinical practice and AI-assisted healthcare. This paper utilizes the Grad-CAM approach to visualize the regions of concentration in the predictions for this purpose. Improved accuracy and efficiency in tumor detection and classification can lead to earlier diagnosis, more personalized treatment planning, and ultimately, better patient outcomes.

As we look at the literature, El Abbadi et al. proposed classifying brain tumor data using Singular Value Decomposition (SVD) in a machine learning-based approach. They used 20 normal and 50 abnormal records to evaluate their methods [9]. They claimed to achieve 96.66% accuracy, 90% sensitivity, and 98% specificity. Basthikodi et al. employed a Support Vector Machine (SVM) as the primary classification method, enhanced by feature extraction techniques like Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP), and Principal Component Analysis (PCA) for dimensionality reduction [10]. Their most significant improvement was achieved by combining SVM with HOG, LBP, and PCA, resulting in 96.03% accuracy, 96.00% F1-score, 96.02% precision, and 96.03% recall. Citak et al. stated that in their brain tumor research, they employed three distinct machine learning methods [11]. These algorithms are logistic regression, SVM, and Multi-Layer Perceptrons (MLPs). They consequently obtained 86.7% specificity, 96.4% sensitivity, and 93% accuracy. Pareek et al. proposed a technique that first determines if a tumor is present in an MRI image before classifying the type of it [12]. That technique uses 150 T1-weighted MRI brain images to detect tumors in the brain. In order to extract features, PCA was used. On top of that, the results of their experiments demonstrate that kernel based SVM has a 97% accuracy rate when it comes to brain tumor classification. Ayadi et al. suggested a technique to raise the quality of MRIs [13]. In the feature extraction step, they used normalization, densely accelerated powerful features, and gradient histogram approaches. During the classification step, they employed a support vector machine. Their approach had an accuracy of 90.27%. They obtained their results via rigorous statistical analysis, which proves the robustness and reliability of the recommended approach.

The growing interest in deep learning based approaches for brain tumor detection is driven by the need for more accurate and robust diagnosis methods. Deep learning algorithms have the potential to improve the precision of brain tumor detection and classification using MRI data [14]. Several studies have explored the application of deep learning techniques to this problem, with promising results [15-21]. One of the key benefits of deep learning for brain tumor detection is its ability to automatically learn relevant features from the input data, without the need for manual feature engineering. This allows for more accurate and comprehensive analysis of the complex patterns associated with brain tumors. Recent studies have showcased the utility of deep learning models in various aspects of brain tumor detection, including tumor segmentation, classification, and grading [22-24]. These studies have explored different deep learning architectures, such as CNNs, Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), and have demonstrated their potential to outperform traditional machine learning techniques. Another study proposed a new deep learning model for brain tumor classification in MRI images. The proposed approach was evaluated using two different MRI datasets and three different kinds of brain tumors; the four labels it contains are healthy, meningioma, glioma, and pituitary [25].

In addition to these studies, the literature also identifies several challenges and limitations associated with the use of machine learning and deep learning for brain tumor detection and other biomedical data [26]. These include the need for large, high-quality datasets, the complexity of training and optimizing deep learning models, and the interpretation of the learned features and decision-making processes [26]. The reviewed literature consistently highlights that further development and implementation of machine learning and deep learning technologies are highly promising for advancing brain tumor detection.
In contrast to previous studies that primarily focus on single-model performance or lack explainability integration, this study presents a comparative analysis of diverse multiple state-of-the-art pre-trained deep learning architectures like ResNet50, DenseNet121, MobileNetV2, and ConvNeXtTiny for brain MRI classification. A key contribution of this work is the incorporation of Grad-CAM-based visual explanations to enhance model interpretability, which is critical in clinical decision-making. Unlike many prior works as we mentioned above, we maintain consistent classification layers across all models to ensure a fair comparison and isolate the impact of feature extraction architectures. The results demonstrate that ResNet50 offers superior sensitivity and reliability, while MobileNetV2 and DenseNet121 provide strong performance with minimal false positives. This study not only benchmarks model performance but also emphasizes the importance of explainability and model selection in real-world medical applications.
This paper has four sections. Section 2 details the materials and methods used for the proposed framework, covering the datasets, models, and performance evaluation strategy. Experimental results are presented in section 3. Section 4 contains the study's concluding remarks. All the cited references are shown at the bottom section of the paper.

2. MATERIAL AND METHOD

This section commences with a description of the datasets utilized proceeds with a detailed explanation of the proposed models and strategy of performance evaluation.

2.1. Brain Tumor Dataset

In this study, a publicly available dataset of brain images from the Kaggle platform is used for training [27]. The dataset comprises healthy and tumor image samples. Of the 4600 images in the dataset, 2500 images possess symptoms of a tumor, while 2087 images reveal no evidence of a tumor or are healthy. Samples in the dataset have different resolutions. We set them with the required input size for the pre-trained models we used.
Another publicly available dataset obtained from the Kaggle, specifically curated, was employed for testing [28]. The dataset includes MRI scans divided into four categories: meningiomas, gliomas, pituitary tumors, and healthy brains. The dataset consists of 3264 images, split into training and testing sets. For tumorous and non-tumorous categories, 220 images were used, with 115 from the meningiomas class and 105 from the healthy class.

2.2. Pre-Trained Deep Models

In this study, we fine-tune deep models and propose these models for the classification of brain tumor images. The block diagram of the proposed method is depicted in Figure 1. It illustrates the end-to-end pipeline developed for brain tumor classification using pre-trained deep learning models. As seen in Figure 1, the selection of the brain tumor dataset, pre-processing of MRI images, feature extraction and classification, and the visualization of the related tumor regions seen by deep learning models are the major steps in this study. The process begins with a labeled dataset of MRI brain images, which forms the foundation for both training and evaluation. After undergoing preprocessing, images from the dataset are fed into one of the pre-trained deep neural networks. These pre-trained models, originally trained on large-scale datasets like ImageNet, are MobileNetV2, DenseNet121, ConvNeXtTiny, and ResNet50, which use transfer learning to extract high-level visual features. They are fine-tuned to learn discriminative features specific to brain tumor classification. The extracted features are passed through custom classification layers to provide final predictions indicating the presence or absence of a tumor. The output from classification layers shows whether the brain is normal or it has a tumor. In addition, Grad-CAM is applied to enhance model interpretability. It is used to provide visual explanations of the model's decision by generating heatmaps over MRI images, highlighting regions that significantly contributed to the classification. This offers critical insights for medical validation and clinical trust. Overall, the figure effectively encapsulates the integration of transfer learning and customized layers with interpretable framework for automated brain tumor detection.

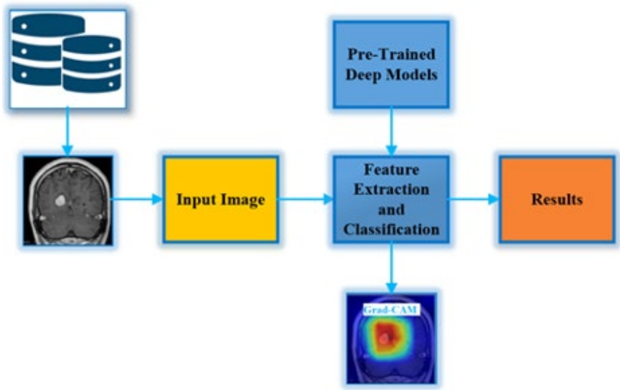

Figure 1. Block diagram of the proposed methodology

Deep learning involves building a feature hierarchy directly from raw input data through multi-layer neural networks [29, 30]. Unlike traditional machine learning, which relies on manual feature extraction, deep learning automates this process, particularly in image analysis. Advances in hardware technology not only facilitate the rapid processing of massive datasets but also contribute to achieving high accuracy and effective generalization. In this study, we used four different pre-trained models and fine-tuned them with the same custom layers. Pre-trained models offer significant advantages, such as faster training times and reduced computational resource requirements, which facilitate the development of AI-based solutions. In this context, we utilized pre-trained ResNet50, MobileNetV2, Dense121, and ConvNeXtTiny models for the implementation of this study. In order to avoid complexity, in this section we only show how to create custom layers using the same parameters for all the models, based on ResNet50 model which acquired better results compared to other models. Figure 2 depicts a pre-trained ResNet50 backbone and custom classification layers stacked onto it to design a complete end-to-end deep learning framework. In addition, we used the same learning rate as 0.00001 and epoch number as 80 for all models.

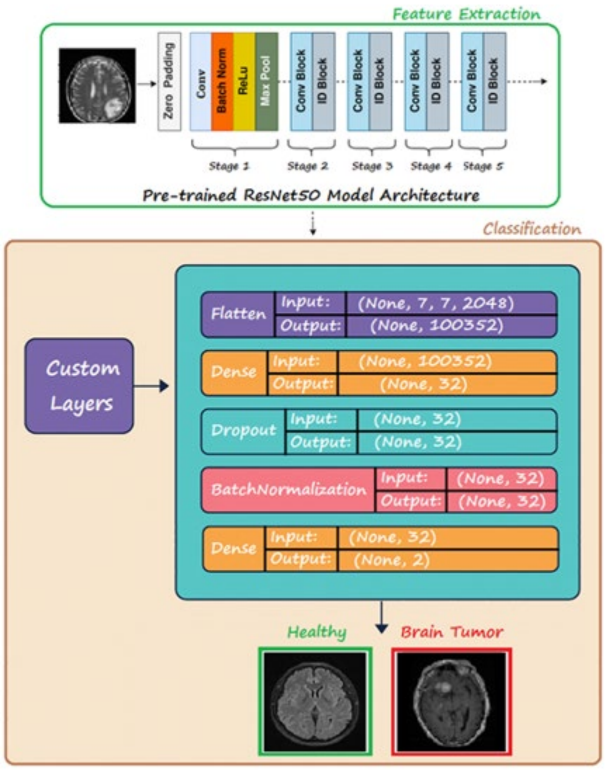

Figure 2. The general framework of deep learning-based learning procedure

As seen from Figure 2, it is clear to have an understanding for the general framework of deep learning based learning procedure. In the feature extraction part, there are convolutional blocks, identity blocks, and activation layers that transform the raw image into a compact feature map of shape (7, 7, 2048). The extracted features are then flattened into a one-dimensional vector and passed through a set of custom layers designed to figure out the final classification. These include a dense layer that reduces dimensionality, a dropout layer with 0.5 value to prevent overfitting, and batch normalization to stabilize training. Finally, there's another dense layer with a softmax activation that gives the probabilities for each class, which is basically showing whether the brain is healthy or has a tumor.

2.3. Performance Evaluation Strategy

Performance evaluation metrics in classification are essential for systematic and objective measurement of a model's discriminative ability. They transcend a naive assessment of prediction accuracy by clarifying the detailed patterns of classification errors. The deployment of standardized metrics provides a robust framework for inter-model comparison and empirical validation of algorithmic improvements. Consequently, these metrics are the basis for informed model selection, iterative optimization and identification of inherent model limitations, thus promoting the development of robust and reliable classification systems. Accuracy, precision, recall and F1-score are the four performance measures used in this study to evaluate the classification performance of the models.
Accuracy, considered the most intuitive metric, measures the proportion of correctly classified samples (Equation 1).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

While accuracy is the most intuitive metric, it can be misleading in unbalanced datasets. Precision measures the proportion of true positives among all samples predicted as positive. Equation (2) shows the calculation of precision.

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

Recall or sensitivity measures the proportion of true positive samples that are correctly identified. It is calculated as shown in Equation (3).

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

Recall or sensitivity measures the proportion of true positive samples that are correctly identified. It is calculated as depicted in Equation (4).

$$F1 - Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{4}$$

The experiment is conducted on an MSI PC that has the following specifications: Intel Core I7 7th Generation (7700 HQ) CPU, 16 GB RAM, 1 TB SSD, and an NVIDIA GeForce GTX 1050 (8 GB) graphics card. We employ the Keras and TensorFlow backend libraries in conjunction with the Kaggle platform to carry out the complete experimental investigation.

3. RESULTS AND DISCUSSIONS

Dataset-I and Dataset-II were used for training and testing, respectively. In order to evaluate the performance of these models, we plotted the accuracy and loss graphs for training and validation data. Figure 3 shows the accuracy and the loss results of training and validation for pre-trained deep learning models used in this study. As we look at the graphs in Figure 3, it is clear that all the models show satisfying results. The highest accuracy was obtained with pre-trained ResNet50 backbone based model as 99.93%. The results of MobileNetV2 and Dense121 were closed to each other, which was 98.98%. The lowest accuracy rate was acquired with pre-trained ConvNeXtTiny backbone based model.

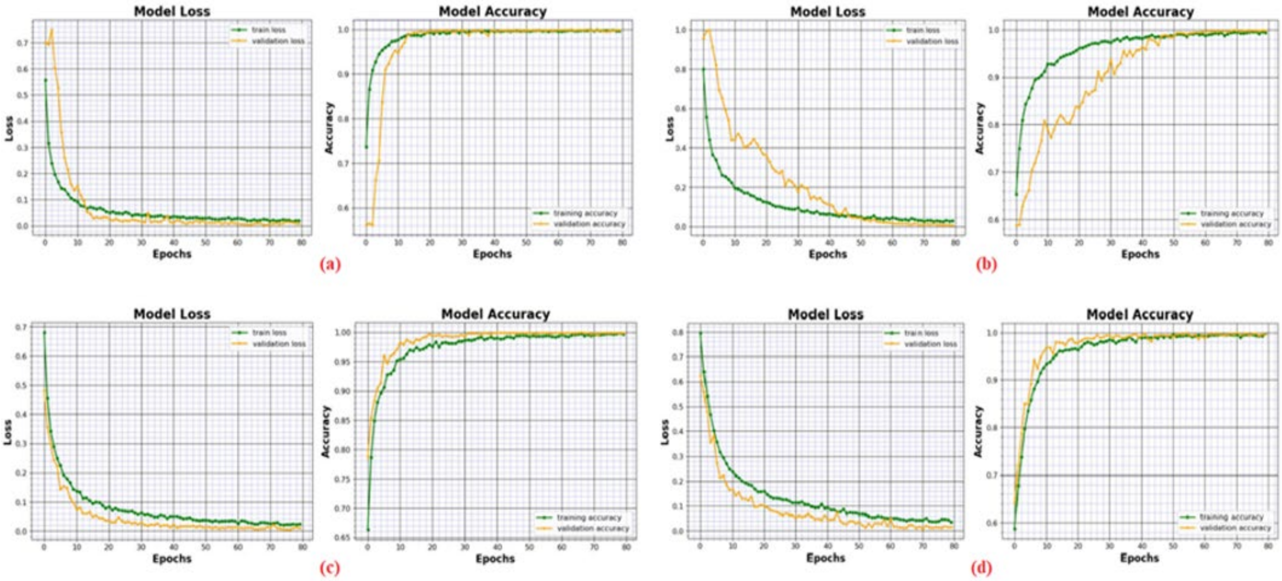

Figure 3. The accuracy and loss curves for training and validation of different deep learning-based classification models: **(a)** ResNet50, **(b)** MobileNetV2, **(c)** DenseNet121, and **(d)** ConvNeXtTiny

The confusion matrix provides a comprehensive overview of an AI-based model's performance by detailing the number of true positives, true negatives, false positives, and false negatives for each class. Figure 4 presents the confusion matrices for the classification of test images using different deep learning models. Each matrix illustrates the model's performance in terms of true positives (correctly classified brain tumor cases), true negatives (correctly classified healthy cases), false positives (healthy cases misclassified as tumor), and false negatives (tumor cases misclassified as healthy).

As shown in Figure 4, the ResNet50 model (a) achieved the highest classification performance, with 113 true positives, 105 true negatives, and only 2 false negatives and 2 false positives. This indicates that ResNet50 is a highly reliable model for both classes. The MobileNetV2 (b) and DenseNet121 (c) models also performed strongly, each achieving 111 true positives and 105 true negatives, with 4 false negatives and no false positives, which is an important factor in clinical practice to avoid unnecessary alarms. In contrast, ConvNeXtTiny (d) demonstrated slightly lower sensitivity, with 107 true positives and 8 false negatives, although it correctly classified all healthy cases.

These results highlight the robustness of the ResNet50 model in tumor detection, followed closely by MobileNetV2 and DenseNet121. They also suggest that even state-of-the-art models like ConvNeXtTiny may require further fine-tuning to optimize sensitivity. Since the custom classification layers were kept consistent across all models, no architectural changes were made to improve individual performance. Overall, all models achieved high classification accuracy, and the slight variations in error rates may guide model selection for practical clinical applications.

Figure 5 shows Grad-CAM visualizations used to interpret the classification decisions of four different pre-trained deep learning models applied to brain MRI images with meningioma tumor and healthy subjects. The first column displays the original labeled input images, while the subsequent columns show the corresponding Grad-CAM heatmaps generated by each model. These heatmaps represent the spatial regions of the input images that contribute most significantly to the classification result. In general, the regions colored in red correspond to the areas where the model focuses its attention heavily. The ResNet50 model demonstrated precise attention to diagnostically relevant factors, reliably localizing tumor regions with sharp, concentrated activation. MobileNetV2 and DenseNet121 also displayed strong activations around tumor areas despite having slightly wider or more diffuse heatmaps. ConvNeXtTiny exhibited more distributed attention, occasionally activating outside of the tumor region. These results confirm the effectiveness of Grad-CAM in improving model interpretability and confirm that deep models not only achieve high classification accuracy but also focus on anatomically meaningful regions. This interpretability promotes the use of AI-assisted technologies in medical imaging diagnostics and is crucial for clinical confidence.

These findings clearly support the effectiveness of using pre-trained convolutional neural networks combined with transfer learning for medical image classification tasks, especially in the context of brain tumor detection from MRI scans. The utilization of pre-trained models such as ResNet50, MobileNetV2, DenseNet121 and ConvNeXtTiny facilitates the exploitation of rich feature representations learned from large-scale datasets such as ImageNet, reducing the need for extensive labeled medical datasets and dramatically boosting the training process. Among the evaluated models, ResNet50 emerged as the most robust and reliable architecture, achieving the highest classification accuracy and providing consistent attention to diagnostically relevant tumor regions as revealed by Grad-CAM visualizations. Its ability to generalize well across different tumor types with minimal false predictions further strengthens its suitability for clinical use. The combination of high prediction potential and interpretable decision making, especially through visual description techniques such as Grad-CAM, makes ResNet50 particularly advantageous in sensitive applications such as radiological diagnosis, where model transparency is critical. A comparison table of the four models' classification performance is given in Table 1.

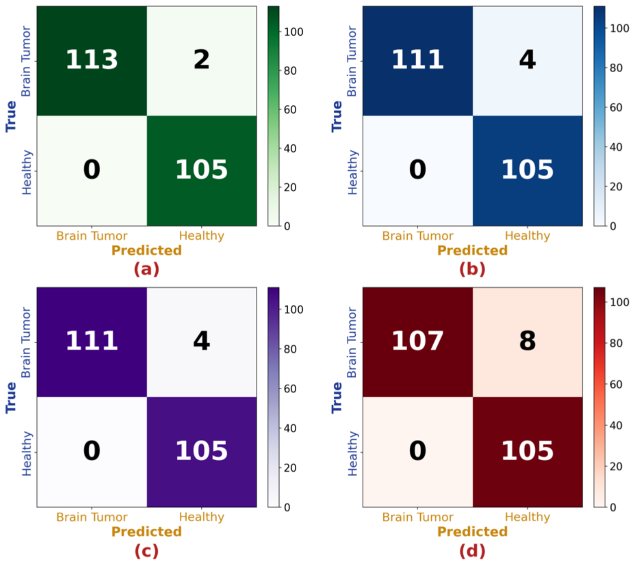

Figure 4. The confusion matrices for classification of test MRI images using different deep learning models: **(a)** ResNet50, **(b)** MobileNetV2, **(c)** DenseNet121, and **(d)** ConvNeXtTiny

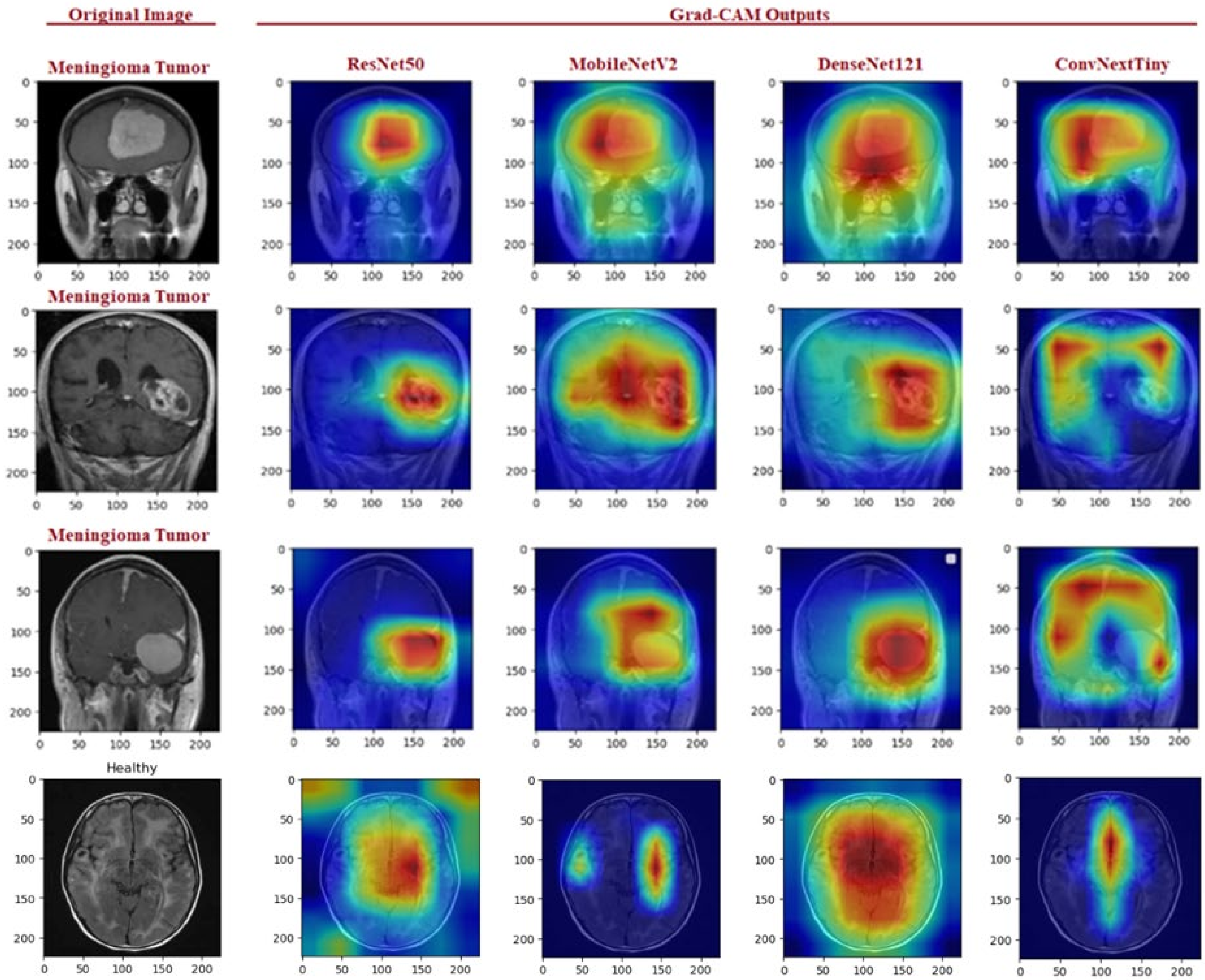

Figure 5. Grad-CAM results obtained for sample test MRI images using pre-trained ResNet50, MobileNetV2, DenseNet121, and ConvNeXtTiny Models

Table 1. A comparison table of the four models' classification performance on the Brain Tumor Detection task

Metric	ResNet50	MobileNetV2	DenseNet121	ConvNeXtTiny
Brain Tumor Precision	100.00%	100.00%	100.00%	100.00%
Brain Tumor Recall	98.00%	97.00%	97.00%	93.00%
Brain Tumor F1-score	99.00%	98.00%	98.00%	96.00%
Healthy Precision	98.00%	96.00%	96.00%	93.00%
Healthy Recall	100.00%	100.00%	100.00%	100.00%
Healthy F1-score	99.00%	98.00%	98.00%	96.00%
Accuracy	99.00%	98.00%	98.00%	96.00%
Macro Avg F1-score	99.00%	98.00%	98.00%	96.00%
Weighted Avg F1-score	99.00%	98.00%	98.00%	96.00%

Although ResNet50 achieved 100% accuracy on our dataset, this should not be considered indicative of universal performance. The dataset was limited in size and drawn from a controlled environment, which may not capture the diversity of real-world clinical scenarios. Factors such as variations in imaging protocols, patient demographics, and equipment can influence model performance. Future work should include external validation on larger, multi-center datasets to assess generalizability.

4. CONCLUSION

The results of this study demonstrate the effectiveness of leveraging pre-trained models with transfer learning for medical image classification and underline how these models might help with radiological diagnosis and facilitate their incorporation into clinical decision support systems.

In this study, the ResNet50 model achieved the highest classification performance with 100% accuracy, showing that it is a highly reliable model for tumor detection. MobileNetV2 and DenseNet121 both performed strongly with 99.89% accuracy. ConvNeXtTiny showed a slightly lower accuracy of 99.78% compared to the other models. By using fundamental CNN structures, we demonstrated that certain networks were innovative in our experimental results. This means our proposals have helped advance biomedical image classification and created a basis for further study in this area. The utilization of Grad-CAM in enhancing model interpretability can yield focusing on anatomically meaningful regions and that will support assisting radiologists with reliable second opinions and providing visual cues that align with expert interpretation, such AI-driven systems can enhance diagnostic confidence, reduce workload, and ultimately contribute to more timely and accurate patient care in medical imaging workflows.

One of this study's two main contributions is the creation of a reliable brain tumor detection model. We developed this model quickly and efficiently by leveraging cutting-edge deep learning architectures. The other is the integration of interpretability techniques to enhance the transparency and understand how any test image is seen by deep learning models. In future, we will be focusing on bringing some new insights by using different deep learning models to reduce the utilization of hardware. We also recommended to expand the evaluation of different deep learning models such as ConvMixer and transformers to increase their validation scores. Furthermore, evaluating these models on larger and more diverse MRI datasets will allow us to assess their performance robustness and generalization capabilities and may further illuminate their scalability and potential for broader application domains.

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