

Comparative Analysis of Custom Scratch CNN and EfficientNetB0 for Brain Tumor Classification in MRI

By Ahmet SOLAK

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Abstract

This paper explores the complex task of classifying brain tumors in magnetic resonance imaging (MRI) images using two approaches: a custom-built Convolutional Neural Network (CNN) and a pre-trained EfficientNetB0 model. The dataset includes four classes: glioma, meningioma, pituitary, and non-tumour, providing a comprehensive representation of brain abnormalities. The network used in this study is a CNN architecture specifically designed for brain tumor classification. The model was developed from scratch, taking into account the unique features and complexities of brain imaging data. The aim of this custom architecture is to investigate the potential benefits of a tailored solution for this classification problem. In contrast, the second network uses transfer learning by leveraging the state-of-the-art EfficientNetB0 model, which has been pre-trained on diverse datasets. Transfer learning aims to apply knowledge gained from extensive training on various datasets to a specific task, potentially improving performance and reducing the need for large amounts of task-specific labelled data. Rigorous experiments and evaluations were conducted on a carefully curated dataset using standard metrics, including accuracy, precision, recall, and F1-score, to assess the performance of both models. The results consistently demonstrate that the EfficientNetB0 model outperforms the scratch CNN across all metrics, indicating its advanced capability in accurately classifying brain tumor images. This study examines the effectiveness of transfer learning in brain tumor classification and highlights the benefits of using a pre-trained model such as EfficientNetB0. The results presented in this paper contribute significantly to the ongoing discussion on the best approach for deep learning-based medical image classification tasks. These findings have the potential to improve diagnostic accuracy and reduce the challenges associated with data annotation efforts.

Keywords: Brain Tumor Classification, Convolutional Neural Network (CNN), Transfer Learning, EfficientNetB0, Medical Image Analysis

1. Introduction

The spectrum of brain tumors, ranging from gliomas and meningiomas to pituitary adenomas, presents a complex and challenging landscape for accurate diagnosis and timely intervention. It is crucial to precisely detect and classify these tumors on magnetic resonance imaging (MRI) as it directly affects treatment planning and patient outcomes. Gliomas, which are characterized by aggressive nature, require early identification for optimized therapeutic strategies, while meningiomas, which are typically benign but can cause potential complications, emphasize the importance of meticulous classification. Pituitary adenomas, which are often hormonally active, further emphasize the need for careful detection to guide specific interventions. The emergence of advanced MRI technologies has revolutionised the field of diagnosis by providing unique insights into the anatomical and pathological characteristics of these tumours [1, 2].

The classification of brain tumors is a crucial effort in the medical diagnosis field, which has profound effects on patient prognosis and treatment planning. Accurate and timely identification of tumor types such as glioma, meningioma, pituitary, and non-tumor is essential to guide health interventions. However, this task is inherently complex and requires a meticulous analysis of complex imaging data. In recent years, the integration of artificial intelligence (AI) techniques, particularly deep learning algorithms, has revolutionised brain tumour classification [3, 4]. The significance of AI in this context lies in its ability to distinguish subtle patterns and features in medical imaging data, surpass traditional methods, and significantly improve diagnostic accuracy.

This paper explores the classification of MRI images in a dataset that includes glioma, meningioma, pituitary, and non-tumor classes. The study involves developing a scratch model based on a convolutional neural network (CNN) [5], a deep learning method, and applying transfer learning using the EfficientNetB0 model [6]. The paper presents a comparative analysis and interpretation of the results obtained from these two models. The paper is structured as follows: the second section explains the materials and methods used in the study, the third

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sect 3 presents the study results and includes a discussion, and the concluding section summarises the findings and presents the conclusion.

2. Materials and Methods

2.1. Dataset

The study employed a dataset comprising four distinct classes: glioma, meningioma, pituitary, and non-tumour [7]. Table 1 displays the number of images used in each class during training, validation and testing phases. Figure 1 provides examples of the MRI images included in the dataset.

Table 1. Class image counts

Class	Train Images	Validation Images	Test Images
Glioma	1123	198	300
Meningioma	1139	200	306
Pituitary	1239	218	300
Non-tumour	1355	240	405

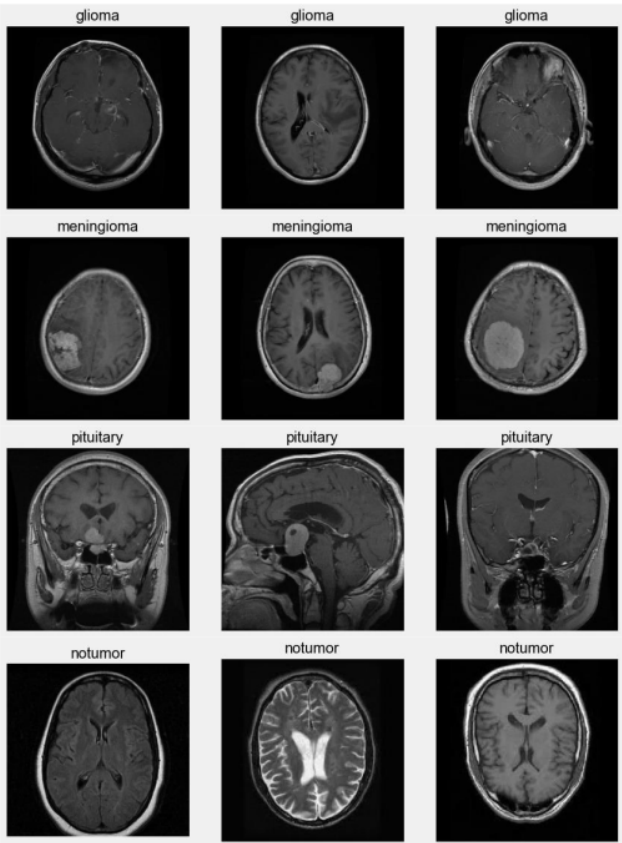


Figure 1. Sample images of each class in the dataset.

2.2. Methods

This study utilized two distinct methodologies for the classification of brain tumor images: a custom-designed Convolutional Neural Network (CNN) architecture and EfficientNetB0, a widely adopted model within the domain of transfer learning.

The architectural details of the scratch CNN model are illustrated in Figure 2. The image processing sequence involves the traversal of four convolutional blocks, culminating in the determination of image classes through subsequent smoothing and classification stages. The convolutional component employs 3x3 filters, 2x2 filters in the max-pooling phase, and a dropout rate of 0.3. Additionally, Rectified Linear Unit (ReLU) [8] activation is employed in the convolution stage, while the softmax activation function is utilized in the classification stage. Within each convolution block, two successive convolutional operations are executed, and the allocated number of filters is as follows: (128,64) in the first convolution block, (64,64) in the second convolution block, (128,128) in the third convolution block, and (128,256) in the final convolution block.

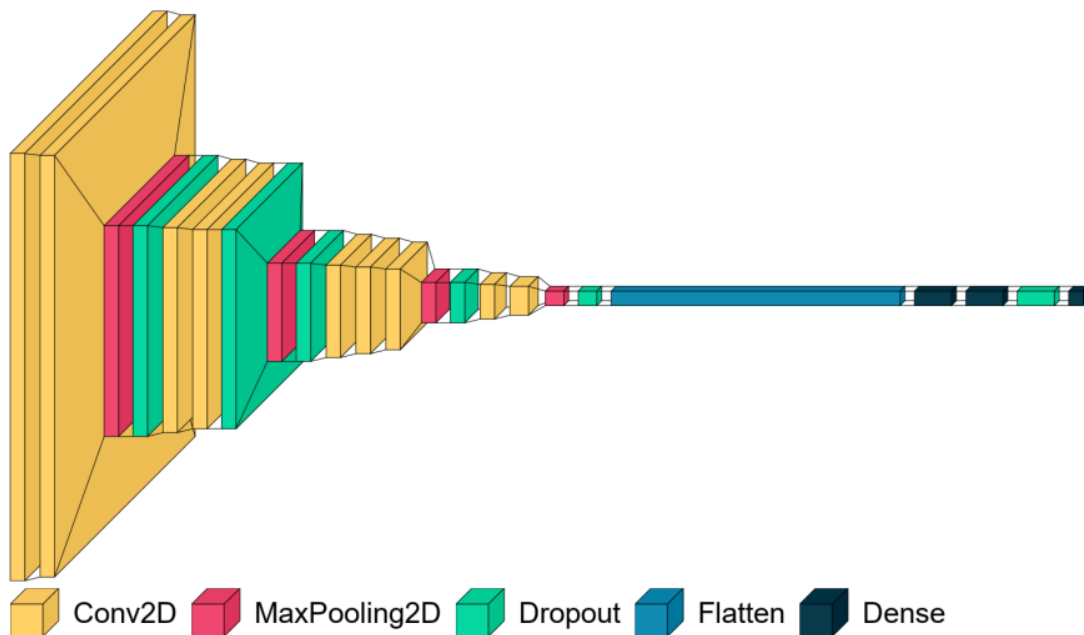


Figure 2. The convolutional neural network (CNN) architecture developed from scratch and utilized in this study.

Transfer learning is a machine learning technique that involves using knowledge gained from training a model on one task and applying it to a different but related task [9]. In the context of deep learning, transfer learning has proven to be especially effective. Pre-trained models on large datasets can capture general features and patterns that are useful for a variety of tasks. One notable example of transfer learning in image classification is the EfficientNetB0 model. EfficientNetB0 belongs to a family of convolutional neural network architectures that are designed for efficient scaling and achieving state-of-the-art performance with significantly fewer parameters than traditional models. It has been pre-trained on diverse datasets and excels in extracting hierarchical features, demonstrating superior generalization abilities. EfficientNetB0 is an appealing option for computer vision tasks, especially in medical image classification where labelled data may be scarce. Its ability to balance computational resources and model complexity contributes to improved performance and reduces the need for extensive task-specific labelled data. The use of EfficientNetB0 in transfer learning also enables the transfer of learned knowledge to specific tasks [10-12].

To facilitate the integration of the EfficientNetB0 model into the classification study, it necessitates adaptation to align with the study's specific requirements. This adaptation process involves populating the convolutional components of the model with pertinent information from prior training, and subsequently configuring the classification layer in the terminal section to suit the characteristics of the study. The adapted segment is visually represented in Figure 3. Functionally delineated in this context is the essential backbone of EfficientNetB0, followed by sequential incorporation of flatten, dropout, and dense layers designed for the purpose of classification.

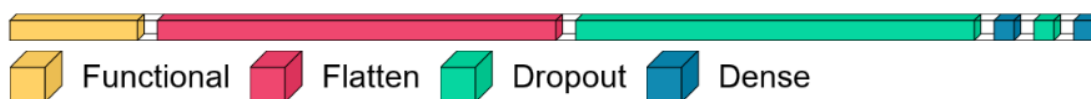


Figure 3. Adaptation of the EfficientNetB0 model to classification study.

3. Results and Discussion

The scratch CNN and EfficientNetB0 architectures were used for classification training. Both training stages used the same hyperparameters, which were an input size of 150x150, 100 epochs, and a batch size of 32.

The CNN model was used to classify brain tumours. The training accuracy was 99%, and the validation accuracy was approximately 86%. The training loss was around 0.02%, but the validation loss remained above 51%. During the testing phase, the network's performance was evaluated based on images that were not used during the training process. Table 2 presents the precision, recall, and F1 score obtained for each class in the tests. Additionally, the confusion matrix for each class, which shows the number of correct and incorrect classifications, is presented in Figure 4.

Table 2. Test results for CNN

Class	Precision	Recall	F-1 Score
Glioma	0.73	0.96	0.83
Meningioma	0.93	0.61	0.74
Non-tumour	0.98	0.93	0.96
Pituitary	0.87	0.96	0.91

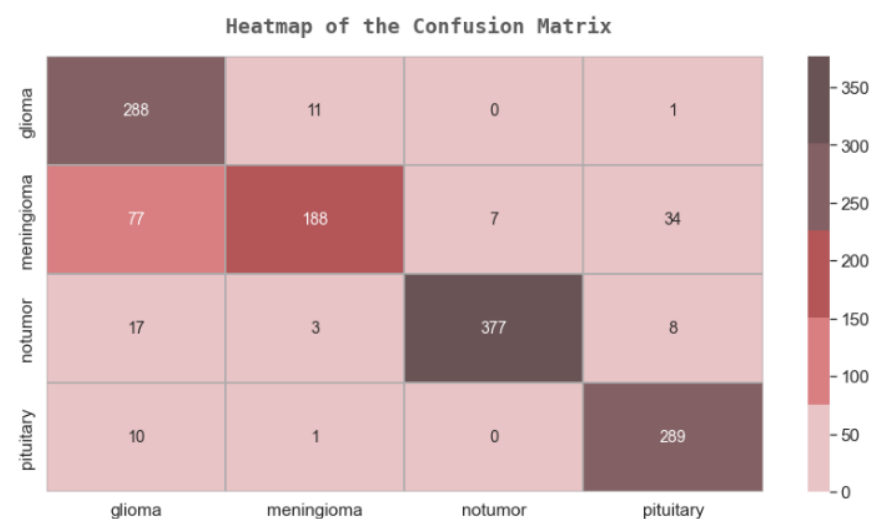


Figure 4. Confusion Matrix for CNN.

In the second phase of the study, similar trainings were carried out with EfficientNetB0 this time. As a result of the trainings, it was observed that while the training accuracy was 99%, the validation accuracy was 95%, while training loss was 0.01%, the validation loss was around 24%. In the test phase, the results obtained for precision, recall and f1 score metrics are shared in Table 3. For better interpretation of these results, the confusion matrix is given in Figure 5. From here, information about how many of the images belonging to which class are correctly or incorrectly classified can be accessed.

Table 3 Test results for EfficientNetB0

Class	Precision	Recall	F-1 Score
Glioma	0.97	0.95	0.96
Meningioma	0.94	0.94	0.94
Non-tumour	0.99	0.99	0.99
Pituitary	0.97	0.99	0.98

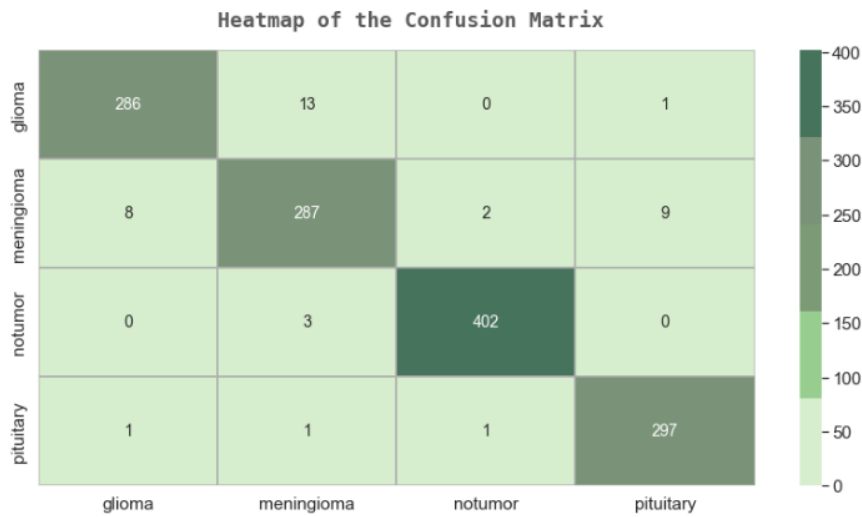


Figure 5. Confusion Matrix for EfficientNetB0.

Upon examining the tables and confusion matrices resulting from both trainings, it is evident that the studies conducted with EfficientNetB0 outperformed the other study. Therefore, it can be concluded that transfer learning is superior to a CNN model trained from scratch.

4. Conclusion

This study proposes the use of deep learning for the diagnosis and classification of brain tumour types, which is crucial for patient health. The study utilises scratch CNN and EfficientNetB0 models to observe changes in classification accuracy and draw inferences about the superior model. The study results demonstrate that transfer learning yields more successful outcomes than training a model from scratch. This finding can serve as a reference for future brain tumour classification studies.

Further research could explore the impact of varying activation functions, batch sizes, and filter numbers on classification performance.

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