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Avaliação do uso de *transfer learning* para detecção de tumores cerebrais em imagens médicas

Evaluation of transfer learning for brain tumor detection in medical images

Evaluación del aprendizaje por transferencia para la detección de tumores cerebrales en imágenes medicas

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Resumo

Objetivo: Com aumento da viabilidade da aplicação das neurais convolucionais (CNNs) foi objetivado avaliar o uso de desta tecnologia para a detecção de tumores cerebrais em imagens de ressonância magnética computadorizada **Método:** Foram desenvolvidos dois modelos distintos de CNNs, uma com o uso de *Transfer learning* e outra sem, para classificar a ocorrência de tumor cerebral. **Resultados:** foi obtido, com o modelo sem o uso de *transfer learning* uma acurácia de 99,67%, com sensibilidade de 100% e especificidade de 99,34%; já com o modelo que usou *transfer learning*, obteve uma acurácia de 98%, com sensibilidade de 98,32% e especificidade de 97,69%. **Conclusão:** Este estudo destaca a eficácia das CNNs na detecção de tumores cerebrais, sugerindo o uso de sistemas inteligentes como ferramentas de auxílio.

Descritores: Tumor Cerebral; Rede Neural Convolucional; *Transfer Learning*.

Abstract

Objective: With the increased feasibility of applying convolutional neural networks (CNNs), the goal was to evaluate the use of this technology for detecting brain tumors in computerized magnetic resonance images. **Method:** Two distinct CNN models were

developed, one using transfer learning and the other without, to classify the occurrence of brain tumors. **Results:** The model without transfer learning achieved an accuracy of 99.67%, with a sensitivity of 100% and specificity of 99.34%. The model using transfer learning achieved an accuracy of 98%, with a sensitivity of 98.32% and specificity of 97.69%. **Conclusion:** This study highlights the efficacy of CNNs in detecting brain tumors, suggesting the use of intelligent systems as auxiliary tools.
Keywords: Brain Tumor; Convolutional Neural Network; Transfer Learning.

Resumen

Objetivo: Con el aumento de la viabilidad de la aplicación de redes neuronales convolucionales (CNNs), se objetivó evaluar el uso de esta tecnología para la detección de tumores cerebrales en imágenes de resonancia magnética computarizada. **Método:** Se desarrollaron dos modelos distintos de CNN, uno con el uso de transferencia de aprendizaje y otro sin ella, para clasificar la ocurrencia de tumores cerebrales. **Resultados:** Se obtuvo, con el modelo sin el uso de transferencia de aprendizaje, una precisión del 99,67%, con una sensibilidad del 100% y una especificidad del 99,34%; con el modelo que usó transferencia de aprendizaje, se obtuvo una precisión del 98%, con una sensibilidad del 98,32% y una especificidad del 97,69%. **Conclusión:** Este estudio destaca la eficacia de las CNN en la detección de tumores cerebrales, sugiriendo el uso de sistemas inteligentes como herramientas auxiliares.
Descriptores: Tumor Cerebral; Red Neuronal Convolucional; Aprendizaje por Transferencia.

Introduction

In the human body, cells are born, grow, and die, being replaced by new cells. If a cell is born before its predecessor dies, a tumor can arise. Brain tumors, also known as intracranial tumors, are classified as benign or malignant, based on their growth rate and recurrence post-treatment. (1,2) .

Benign tumors grow slowly and have low recurrence, while malignant tumors, predominantly composed of cancer cells, can infiltrate adjacent tissues, and spread throughout the body in a process called metastasis. They can be primary, originating in brain tissue, or secondary, arising from other parts of the body (3). Due to their severity, brain tumors pose a serious risk to human health, accounting for nearly 227,000 deaths annually, according to the Global Burden of Disease (4,5). Diagnosis is challenging due to the blood-brain barrier, with magnetic resonance imaging and computed tomography being the best imaging methods to detect alterations in this barrier (6,7). Manual diagnostic accuracy has a maximum expert agreement of 90% to 95% (6). With the advancement of imaging technologies and digital processing, computer-aided diagnosis has become more common (6).

Convolutional neural networks (CNNs) have become a viable possibility when it comes to assisting in image-based diagnosis. Consequently, they are widely implemented in solutions aimed at assisting specialized professionals. (8–10).

In Naseeret al. (6), a computer-aided brain tumor diagnosis tool was proposed to examine brain MRIs and provide early diagnosis with improved performance, characterized as a computer-aided diagnosis (CAD) system. In the model proposed by the authors, a CNN was used along with image preprocessing for better performance. On average, the model provided 98.81% correct diagnosis of brain tumors. In this same article, the author discussed the need for more advanced visualization tools to better analyze the results.

Papageorgiou(11) proposed a tool to classify MRI images. his proposed classification is binary and uses a low-complexity CNN. This model achieved accuracy of 99.62% using cross-validation. Papageorgiou et al. (12), categorized high-grade and low-grade gliomas based on diffuse cognitive maps and achieved 93.22% and 90.26% accuracy for high-grade and low-grade brain tumors, respectively.

In addition to conventional CNNs, a powerful technique that has been widely used in machine learning tasks is transfer learning. (13–15). Transfer learning allows pre-trained models on large datasets to be reused as a basis for solving similar or related tasks. Rethemiotaki (1) used brain MRI images divided into 4 categories: unspecified glioma, meningioma, pituitary tumor, and healthy brain. Twelve convolutional neural networks (GoogleNet, MobileNetV2, Xception, DenseNet-BC, ResNet-50, SqueezeNet, ShuffleNet, VGG-16, AlexNet, Enet, EfficientB0, and MobileNetV2 with pseudo-labels) were employed to classify these images. Experimental results show that the MobileNetV2 CNN model was able to diagnose brain tumors with 99% accuracy, 98% recall, and 99% F1 score. On the other hand, validation data analysis shows that the GoogleNet CNN model has the highest precision (97%) among CNNs and appears to be the best choice for brain tumor classification. In Kang (16), a method for brain tumor classification was presented using the feature sets of pre-trained CNNs to quantify the best existing network for the size of the database. It concluded that the feature set of DenseNet-169, Inception V3, and ResNeXt-50 is a good choice if the MRI dataset size is large and the number of classes is 2 (normal, tumor) (11). However, these results were shown for an average of 9 classifier patterns. In the case of an analysis solely of sigmoid classifiers, the four best model were ResNet-50, ResNet-101, AlexNet, and MnasNet (2).

This study aims to explore methods for detecting brain tumors in magnetic resonance imaging (MRI) using Convolutional Neural Networks (CNNs), for the creation of a decision support system. The distinction of this work, compared to those previously mentioned, lies in the following points: Comparative evaluation of the effectiveness of CNN models with and without the use of transfer learning, where all model parameters are estimated during the training process without transfer learning; Generation of heat maps to identify the regions activated by the generated artificial intelligence model using Grad-CAM techniques, providing a visual interpretation of the areas of interest identified by the models.

To evaluate the performance of these models, the Br35H(17) dataset was used, which contains magnetic resonance images of brain tumors classified into two distinct categories: tumorous and non-tumorous.

This study not only tests the effectiveness of approaches with and without transfer learning but also investigates the impact of each method on detection accuracy, providing a comprehensive and interactive analysis of a decision support system using CNNs in the medical field.

Methods

For the implementation of this work, Python language was used. In this implementation, the Keras library was used, which is an API of TensorFlow, enabling the creation and training of learning models.

Dataset

The Br35H dataset (14) is composed by MRI images, divided into two categories: "yes" and "no", with the "yes" category being images with a positive diagnosis for the presence of an intracranial tumor and "no" diagnosis, negative for intracranial tumor. These images were collected from patients with various types of brain tumors, encompassing both benign and malignant tumors, including pituitary tumors, among others.

The database contains about 3000 MRI images, with 1500 positive for brain tumors and 1500 negative. Since this database was already balanced. For standardization purposes, the images were resized to 240 x 240 format with the number of layers ranging from 1 to 3 according to the rest of the architecture of evaluated CNN. About 20% of dataset (600 images) are randomly separated for test the proposed models.

The remain data were used to train and validate de model. K-folds cross-validation (CV) technique was used with. k = 3, This technique was employed to evaluate the results to check the model's stability, considering the differentiation of training in each validation subset.

Architectures

The CNN architecture has three basic layers: the convolutional layer, the pooling layer, and a fully connected layer. In the first stage, convolution extracts features from the images, generating an output tensor. Then, pooling simplifies this information, reducing the dimension of the output. After repeating this process, the images are vectorized and passed to the fully connected layer, responsible for the final classification.

Convolutional Neural Network.

The convolutional layers were initially based on Papageorgiou (18), utilizing two convolutional layers with 32 filters and the ReLU activation function, followed by maxPooling layers. Additionally, as suggested by Naseer A. (6), a dropout layer was added after the MaxPooling layers.

The CNN architecture was defined sequentially, and the constructed model is represented in Figure 1.

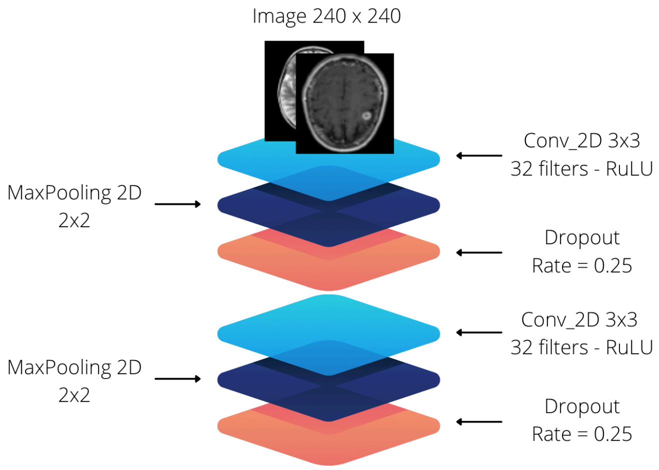

Figure 1 – Convolutional model architecture without transfer learning.

As training a CNN for feature extraction can often be slow and difficult due to many optimization parameters, we tested the Transfer Learning technique, with the use of a pre-trained CNN, as described in Figure 2. Since Transfer Learning assumes that if two models are developed to perform similar tasks, generalized knowledge can be shared between them, we sought the network that best fits MRI images. According to Kang the model that showed the highest accuracy using Br35H dataset was ResNet-50 using the Sigmoid classifier. However, as there is a newer version of this pre-trained network, we opted to use the latest version of this model, ResNet-50V2.

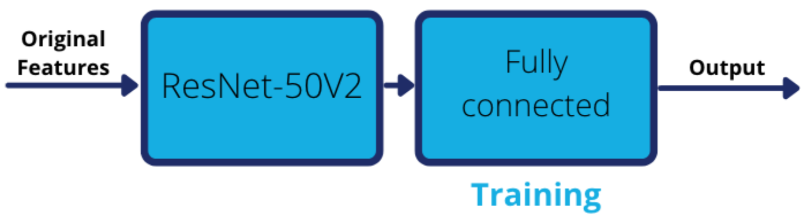

Figure 2 – General architecture of the network for the use of transfer learning.

Fully Connected Layer

After the feature extraction layers, a flattening technique is defined for the network output followed by two fully connected dense layers with 500 and 1 units. ReLU and Sigmoid are used as activation functions in these fully connected layers, respectively. The CNN architecture was implemented equally for both models, which is illustrated in Figure 3.

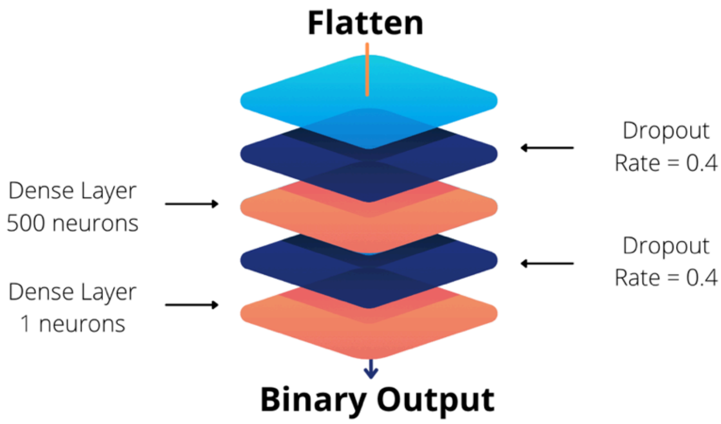

Figure 3 – Fully connected layer architecture.

In this study, we updated the layer weights via Adaptive Moment Estimation (Adam), an optimizer that computes adaptive learning rates for each parameter. The learning rate is set to 0.0001. We ran each of the methods for 30 epochs. We collected the highest average accuracy for our test dataset for each run.

Model performance metrics

The performance of proposed models was evaluated by accuracy, sensitivity, specificity, and AUC (Area under the ROC curve) variables. Additionally, he Grad-CAM (Gradient-weighted Class Activation Mapping) technique is used to visualize the important regions images that influence the decisions of the CNNs (19)

The basic idea of Grad-CAM is to generate an activation map that highlights the regions of the image most relevant to the classification performed by the CNN. This is achieved by calculating the gradient of the desired output with respect to the activations of the last convolutional layer of the network. The gradient is then weighted by the importance of these activations and used to generate the activation map, highlighting the most influential regions for classification.(19)

Results

The training data and specific results for each fold of cross-validation for both models are available in Table 1. Additionally, the loss and accuracy curves for each fold of cross-validation can be visualized in graphic 1 for the CNN without transfer learning and in graphic 2 for the CNN with transfer learning.

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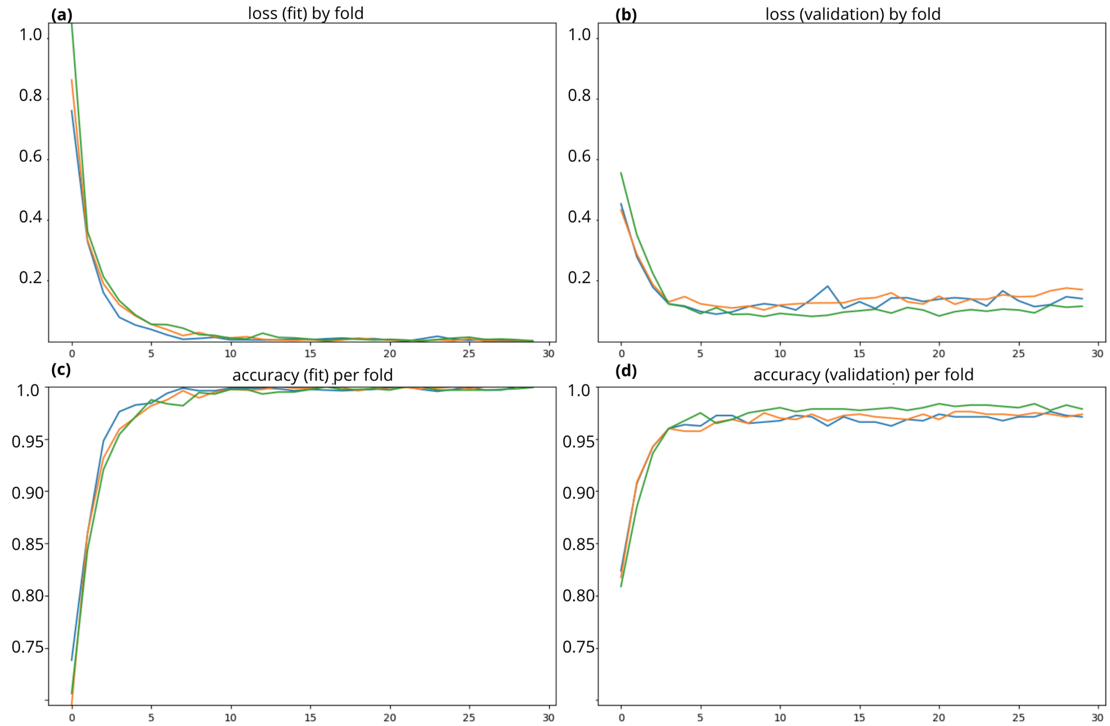
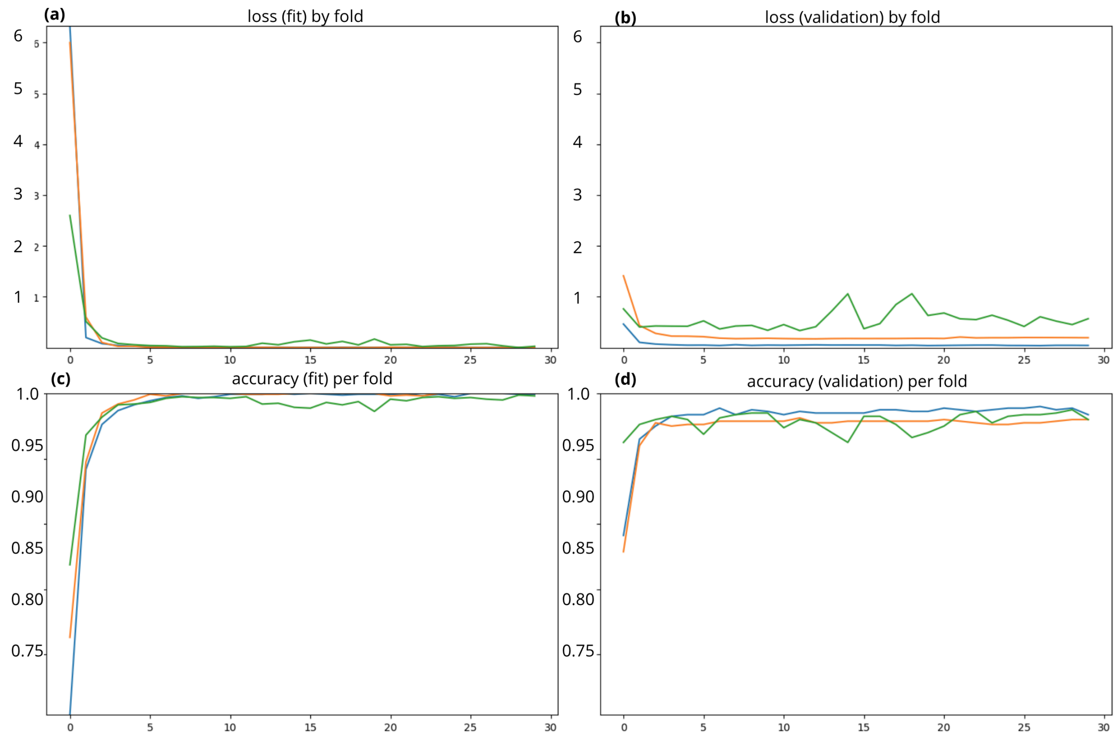
	(a) Model without Transfer Learning			(b) Model with Transfer Learning:		
	Accuracy	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**
Fold 1	97.94%	97.94%	96.34%	98.26%	98.26%	98.48%
Fold 2	97.34%	97.34%	97.40%	97.78%	97.78%	98.22%
Fold 3	97.70%	97.70%	98.03%	97.25%	97.25%	98.74%
Mean	97.66%	97.66%	97.26%	97.76%	97.76%	98.48%
variance	0.092%	0.092%	0.736%	0.253%	0.253%	0.068%

Table 1 – Validation values of CNNs by fold. (a) Model that did not use transfer learning. (b) Model that used transfer learning to extract features



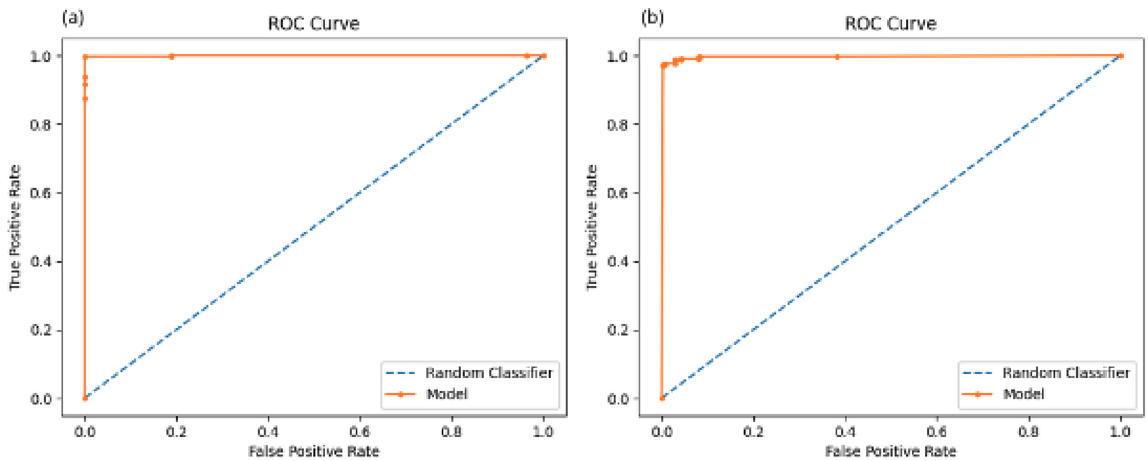
Graphic 1 –. CNN learning curves. training loss curve in each, validation loss curve in each fold in 30 epochs, training accuracy curve per fold in 30 epochs and validation accuracy curve per fold in 30 epochs.



Graphic 2 – CNN learning curves using transfer learning. (a) training loss curve in each fold over the 30 epochs, (b) validation loss curve in each fold over the 30 epochs, (c) training accuracy curve per fold in 30 epochs and (d) accuracy curve in fold validation in 30 epochs.

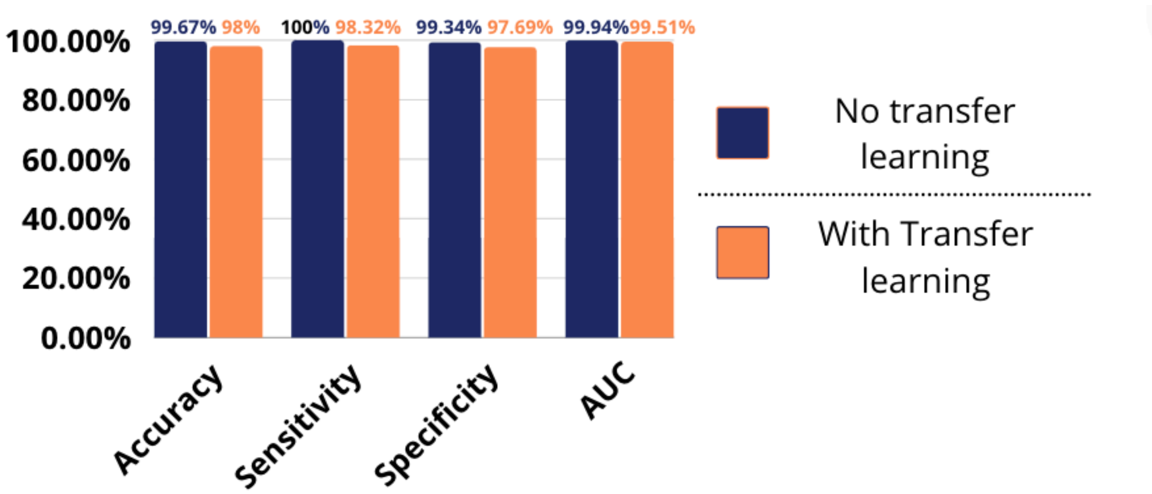
After conducting a T-test with cross-validation to compare the two proposed models, based on accuracy across three folds, it was observed that there is no statistically significant difference between their performances ($T \approx 0.3977$, $p > 0.05$). The first network exhibited an average accuracy of 97.66% (standard deviation of 0.287%), while the second network achieved an average accuracy of 97.76% (standard deviation of 0.328%). Therefore, there is insufficient evidence to reject the null hypothesis that there is no significant difference between the two networks.

The final models were also compared using the test data subset. Graphic 3 presents the ROC curves, which corresponds to AUC of 99.94% for the model without transfer learning and 99.51% for the model with transfer learning. Graphic 4 compares the performance metrics the models.



***Graphic 3 –** ROC curve of CNN model test data. (left) Model that did not use transfer learning. (right) Model that used transfer learning to extract features*

For the comparison of the two CNNs, the network without the use of transfer learning had a slight edge over the network without pre-training because its four indicators were more qualified, as can be seen in Figure 4. However, this difference, as indicated by the t-test, by the p-value, appears to be insignificant and consistent with the results achieved in the literature. However, one of the advantages of the model that uses transfer learning is that it does not need to undergo training in the convolutional layers, thus speeding up the processing time of the training process, being around 1 minute per fold for the network without, while the network that used transfer learning took 20 per fold, both being processed on the A100 tensor core GPU.



Graphic 4 – Comparison of the results of accuracy, sensitivity, specificity and area under the ROC curve between the two proposed models.

When applying the Grad-CAM technique with the model without the use of transfer learning, the generated heat map shown in Figure 6.b and Figure7.b exemplifies a true positive case and true negative. On the other hand, when using the transfer learning model with the same input image, the generated heat map shown in Figure 6.c and figure 7.c.

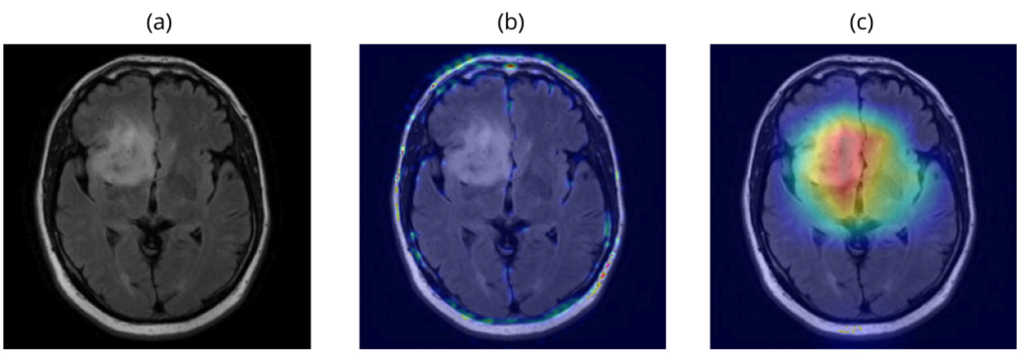


Figure 6 – (a) Positive magnetic resonance image for brain tumor. (b) Heat map superimposed on the MRI image of the model without using transfer learning. (c) Heat map superimposed on the MRI image generated by the model using transfer learning.

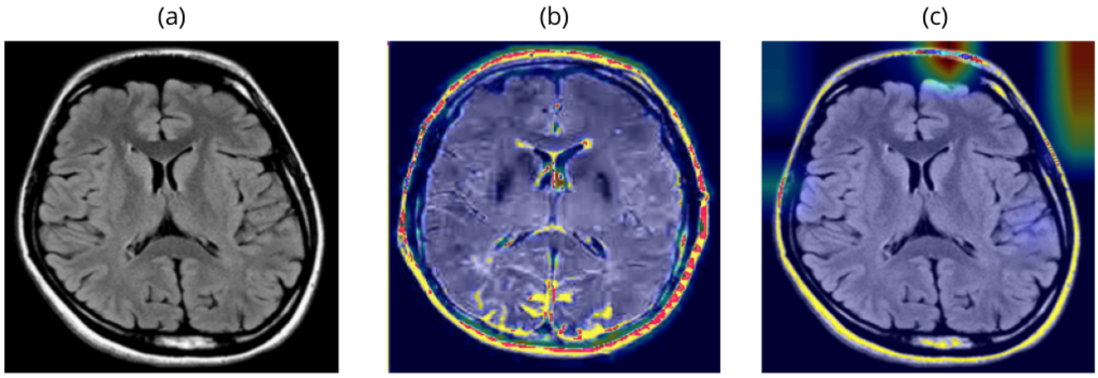


Figure 7 – Negative magnetic resonance image for brain tumor. (b) Heat map superimposed on the MRI image of the model without using transfer learning. (c) Heat map superimposed on the MRI image generated by the model using transfer learning.

Comparing the two models, it became evident that the use of the Grad-CAM technique resulted in a clearer heat map in the model that employed transfer learning. This model accurately highlighted the areas where neurons were activated, indicating the presence of a brain tumor and aligning consistently with the location of the tumor mass. In contrast, the model that did not employ transfer learning failed to generate a visually comparable demonstration for the same image.

Conclusion

Considering the objective of this project to propose a CNN for the detection of brain tumors through magnetic resonance imaging, two models of convolutional neural network architectures were proposed: one with and one without the use of transfer learning. The architectures of these two networks were built based on reference articles.

From the results obtained with both networks, we conclude that both CNNs achieved excellent results. Based on the t-test for the hypothesis of a significant difference in network quality, the result of t = 0.3977 indicated that this difference is not significant. However, the network without the use of transfer learning had a slight advantage in all the metrics analyzed.

The network with the best performance on the test set exhibited an accuracy of 99.67%, sensitivity of 100%, and specificity of 99.34% with the test data (600 images). On the other hand, the network that utilized transfer learning had the advantage of lower computational cost for training, as it is a pre-trained network connected to classification layers.

The comparative analysis of the two models demonstrated the significant advantages of utilizing transfer learning combined with the Grad-CAM technique. The transfer learning model not only achieved a clearer and more precise heat map, highlighting the areas of neuron activation corresponding to brain tumors, but also provided a crucial level of interpretability for medical applications. These results suggest that transfer learning models hold great potential for enhancing diagnostic tools, ultimately contributing to more accurate and reliable medical diagnoses.

References

1. Rethemiotaki I. Brain tumour detection from magnetic resonance imaging using convolutional neural networks. Contemp Oncol [Internet]. 2023 [cited 2024 Apr 21];27(4):230. Available from: /pmc/articles/PMC10883197/
2. Fritz A, Percy C, Jack A. International Classification of Diseases for Oncology. Third. Vol. 1. Switzerland: World Health Organization; 2000. 0–222 p.
3. Tandel GS, Biswas M, Kakde OG, Tiwari A, Suri HS, Turk M, et al. A review on a deep learning perspective in brain cancer classification. Cancers (Basel) [Internet]. 2019 Jan 18 [cited 2021 Dec 12];11(1):111. Available from: https://www.mdpi.com/2072-6694/11/1/111/htm
4. Kang J, Ullah Z, Gwak J. Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers. Sensors [Internet]. 2021 Mar 22 [cited 2021 Dec 12];21(6):1–21. Available from: https://www.mdpi.com/1424-8220/21/6/2222/htm
5. Patel AP, Fisher JL, Nichols E, Abd-Allah F, Abdela J, Abdelalim A, et al. Global, regional, and national burden of brain and other CNS cancer, 1990-2016: a systematic

analysis for the Global Burden of Disease Study 2016. Lancet Neurol [Internet]. 2019 Apr 1 [cited 2024 Apr 22];18(4):376–93. Available from: https://pubmed.ncbi.nlm.nih.gov/30797715/

6. Naseer A, Yasir T, Azhar A, Shakeel T, Zafar K. Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI. Int J Biomed Imaging. 2021;2021.
7. Fernandes SL, Tanik UJ, Rajinikanth V, Karthik KA. A reliable framework for accurate brain image examination and treatment planning based on early diagnosis support for clinicians. Neural Comput Appl [Internet]. 2020 Oct 1 [cited 2024 Apr 22];32(20):15897–908. Available from: https://link.springer.com/article/10.1007/s00521-019-04369-5
8. Naseer A, Yasir T, Azhar A, Shakeel T, Zafar K. Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI. Int J Biomed Imaging. 2021;2021.
9. Naseer A, Zafar K. Comparative Analysis of Raw Images and Meta Feature based Urdu OCR using CNN and LSTM. International Journal of Advanced Computer Science and Applications. 2018;9(1):419–24.
10. Naseer A, Zafar K. Meta features-based scale invariant OCR decision making using LSTM-RNN. Comput Math Organ Theory [Internet]. 2019 Jun 1 [cited 2024 Apr 22];25(2):165–83. Available from: https://link.springer.com/article/10.1007/s10588-018-9265-9
11. Papageorgiou V. Brain tumor detection based on features extracted and classified using a low-complexity neural network. Traitement du Signal. 2021 Jun 1;38(3):547–54.
12. Papageorgiou EI, Spyridonos PP, Glotsos DT, Stylios CD, Ravazoula P, Nikiforidis GN, et al. Brain tumor characterization using the soft computing technique of fuzzy cognitive maps. Applied Soft Computing Journal. 2008 Jan 1;8(1):820–8.
13. Deepak S, Ameer PM. Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med [Internet]. 2019 Aug 1 [cited 2024 Apr 28];111. Available from: https://pubmed.ncbi.nlm.nih.gov/31279167/
14. Wu M, Liu Q, Yan C, Sen G. Multi-Classification of Brain Tumors on Magnetic Resonance Images Using an Ensemble of Pre-Trained Convolutional Neural Networks.

Curr Med Imaging [Internet]. 2022 Apr 18 [cited 2024 Apr 28];19(1):65–76. Available from: https://pubmed.ncbi.nlm.nih.gov/35430973/

15. Swati ZNK, Zhao Q, Kabir M, Ali F, Ali Z, Ahmed S, et al. Brain tumor classification for MR images using transfer learning and fine-tuning. Comput Med Imaging Graph [Internet]. 2019 Jul 1 [cited 2024 Apr 28];75:34–46. Available from: https://pubmed.ncbi.nlm.nih.gov/31150950/
16. Kang J, Ullah Z, Gwak J. Mri-based brain tumor classification using ensemble of deep features and machine learning classifiers. Sensors. 2021 Mar 22;21(6):1–21.
17. Br35H :: Detecção de tumor cerebral 2020 | Kaggle [Internet]. [cited 2021 Dec 12]. Available from: https://www.kaggle.com/ahmedhamada0/brain-tumor-detection
18. Papageorgiou V. Brain tumor detection based on features extracted and classified using a low-complexity neural network. Traitement du Signal. 2021 Jun 1;38(3):547–54.
19. Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization. Int J Comput Vis [Internet]. 2016 Oct 7 [cited 2024 May 27];128(2):336–59. Available from: http://arxiv.org/abs/1610.02391