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Using transfer learning model for brain tumor detection

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RESUMEN

Este trabajo investiga el uso de redes neuronales convolucionales y técnicas de aprendizaje por transferencia para clasificar imágenes de rayos X del cerebro, con especial atención a la detección de tumores. La base de datos utilizada contiene 253 imágenes de resonancia magnética, de las cuales 155 muestran tumores. La metodología incluyó el preprocesamiento de imágenes, como el recorte de bordes y la ecualización de histogramas, seguido del entrenamiento de un modelo VGG-16 previamente entrenado. Los resultados demostraron una exactitud del 93,35% en entrenamiento, lo que pone de relieve la eficacia del enfoque.

Palabras claves: CNN; Computación Visual; Transferencia de Aprendizaje; Tumor; VGG-16.

ABSTRACT

This work investigates using Convolutional Neural Networks and transfer learning techniques to classify brain X-ray images, focusing on tumor detection. The dataset contains 253 magnetic resonance images, of which 155 show tumors. The methodology included image preprocessing, such as edge cropping and histogram equalization, and training a pre-trained VGG-16 model. The results showed an accuracy of 93.35% in training, highlighting the approach's effectiveness.

Keywords: CNN; Computer Vision; Transfer Learning; Tumor; VGG-16.

1 Introduction

According to Pinho Costa et al. (2024), cancer is a term that encompasses more than 100 diseases, all characterized by the uncontrolled growth of cells that invade tissues and organs. The National Cancer Institute (INCA 2024a) states that these cells have an accelerated and usually aggressive division process, resulting in the formation of tumors. The origin of the affected cells defines different types of cancer. For example, when cancer originates in tissues such as the skin or mucous membranes, it is classified as carcinoma. In contrast, it is called sarcoma when it arises in bones, muscles, or cartilage (INCA 2024b).

In 2022, approximately 18 million new cancer cases were diagnosed worldwide, of which around 322,000 were brain cancer, resulting in approximately 249,000 deaths, as reported by Ferlay et al. (2018). In Brazil, estimates for the same period indicate 12,000 new cases of brain cancer.

Due to the aggressive nature of cancer, early detection is crucial to increasing the chances of less invasive treatments with higher success rates, leading to a greater likelihood of cure. For this reason, various initiatives have been adopted to diagnose cancer in its early stages (INCA 2019). The significant increase in the number of cancer cases, combined with the lack of effective methods for its cure, especially in the advanced stages of the disease, is a major concern for global health (Dalvi 2018). Therefore, investing in early diagnosis is essential, as it allows for detecting cancer in its initial stages, increasing the chances of successful treatment.

One way to diagnose brain cancer is through magnetic resonance imaging (MRI), which can identify suspicious changes. Computational techniques have been developed to assist healthcare professionals in classifying these images. According to Buciu and Gacsadi (2011), these techniques can help doctors make more accurate diagnoses.

In a study conducted by Calas, Gutfilen, and Albuquerque Pereira (2012), the use of software to assist radiologists in image classification was evaluated. The study compared two scenarios: in the first, radiologists used the software to support diagnosis, while in the second, they performed the classification without this assistance. The results showed that radiologists' sensitivity without the software was 79%, whereas with the tool's aid, this sensitivity increased to 84%.

Convolutional Neural Networks (CNNs) are a widely used technique for image analysis. A common approach with CNNs is transfer learning, which involves adapting a pre-trained model from a related task to be applied to a new task with a smaller dataset. In transfer learning, the knowledge gained from solving one problem is applied to a different but related problem. This can be particularly useful in medical imaging, where datasets are often limited and the cost of training a model from scratch can be high.

This work aims to develop a transfer learning model for classifying brain cancer in MRI images. CNNs are chosen due to their proven effectiveness in image processing, especially in medical diagnosis tasks. This study applies CNN techniques, exploring transfer learning with the pretrained VGG-16 (Visual Geometry Group architecture with 16 layers) model, aiming to maximize performance in the classification of brain MRI images.

2 Related Works

CNNs are a type of Deep Learning (DL) architecture that includes the convolution operation in at least one of its layers (Goodfellow, Bengio, and Courville 2016). These networks are designed to process data in the form of multiple vectors, such as colored images, which consist of three 2D vectors, each representing the intensity of pixels in different color channels (Neto, Menezes, et al. 2018).

The primary application of CNNs is in processing visual information, particularly images, as convolution allows for handling the two-dimensional structure of this information (Ponti and Costa 2018). CNNs are often more efficient than fully connected networks with the same number of hidden layers.

CNNs have been widely used in various fields. The literature includes works that employ CNNs in diverse applications, such as pedestrian detection (Vargas, Paes, and Vasconcelos 2016), stress identification in cattle vocalizations (Paiva, Ferreira, and Perez 2024), classification of vegetation cover and tree species in tropical urban environments (Souza Silva 2024), and classification of fish species (Pacheco 2019).

In the medical field, the use of CNNs is also widespread. For example, Parella (2024) used CNNs to segment blood vessels, while Oliveira (2023) applied these networks in lung segmentation in chest radiographs. Saifullah and Dreżewski (2023) presented an enhanced segmentation of medical images using CNNs based on histogram equalization, and Nizamani et al. (2023) employed CNNs to segment brain tumors.

Several studies have explored CNNs for classifying MRI images of brain tumors. Özkaraca et al. (2023) used Kaggle databases and different CNN models for this task. Al-Zoghby et al. (2023) proposed a Dual Convolution Tumor Network (DCTN) to classify three types of brain tumors (meningioma, glioma, and pituitary), achieving 100% accuracy in training and 99% in testing. Gupta, Gaurav, and Arya (2024) employed a three-layer CNN to identify brain tumors in Industrial Information Systems, reaching 90% accuracy in the test set. Srinivasan et al. (2024) proposed three distinct CNN models, with the first achieving 99.53% accuracy, the second categorizing tumors into five distinct types with 93.81% accuracy, and the third reaching 98.56% in classifying different grades of brain tumors.

These studies demonstrate the positive impact of CNNs on brain cancer diagnosis. However, the success of using these networks often depends on the availability of large volumes of data for training. One solution to this limitation is using transfer learning, which adjusts pre-trained models for new tasks. According to Chaves (2019), this approach is widely employed in DL models, mainly due to the need for large amounts of data and computational resources to fully train complex models like CNNs.

In order to utilize transfer learning, it is necessary to use models that perform well on the tasks they were designed for. Many established CNN architectures are available in packages or libraries. For example, Keras provides models that have been used to classify ImageNet.

Transfer learning is recommended when the dataset is smaller than the one used to train the pre-trained model. To use a pre-trained CNN as a feature extractor, it suffices to remove the last fully connected layer of the network (the layer that computes the probability of the input image belonging to one of the predetermined classes) and utilize the final output of the new network as the features describing the input image (Araújo et al. 2017).

The studies address the use of CNNs and transfer learning techniques to enhance the analysis of medical images. Salehi et al. (2023) emphasized the advantages of these techniques, such as greater accuracy and efficiency in image classification tasks, especially in scenarios with limited datasets. The reuse of pre-trained models allows overcoming challenges related to data scarcity and computational resources. Burri et al. (2023) also explored the effectiveness of transfer learning, showing that it offers superior performance compared to other image classification techniques, particularly in situations with scarce labeled data, such as Alzheimer's and Coronavirus disease 2019 (COVID-19) diagnostics. On the other hand, Chae and Kim (2023) investigated transfer learning approaches to overcome the limitation of labeled data in tasks like skin lesion detection and cervical cancer classification, demonstrating significant improvements in accuracy and sensitivity, suggesting that these techniques are effective even in scenarios with insufficient data.

Several networks are widely used in the literature for transfer learning, such as VGG-16. According to Araújo et al. (2017), some advantages of using CNNs include extracting relevant features through kernels and requiring fewer examples than VGG-16. Various studies have explored its application in cancer diagnostics, highlighting its effectiveness in multiple tasks. In the work of Hossain, Nisha, and Johora (2023), VGG-16 was employed to classify ultrasound images of breast cancer, utilizing filtering techniques to reduce noise and optimize the model's accuracy, achieving 91% accuracy on test data with the help of Gradient-weighted Class Activation Mapping (Grad-CAM), demonstrating its potential in clinical applications. Similarly, Faghihi, Fathollahi, and Rajabi (2024) combined VGG-16 with VGG-19 and AlexNet to classify skin lesions, significantly improving accuracy from 94.2% to 98.18% without data augmentation.

Furthermore, Bairagi et al. (2023) also utilized VGG-16, among other CNN architectures, to automatically detect brain tumors. This study compared various architectures, adjusting their hyperparameters and achieving 98.67% accuracy in tumor classification from MRI images. The results demonstrated the effectiveness of VGG-16 and other transfer learning techniques in the rapid and accurate detection of tumors, which is crucial for the effective and immediate treatment of patients.

Thus, the choice of VGG-16 in this work is justified by its efficacy in classifying brain tumors. Transfer learning, by allowing the reuse of pre-trained models, offers a viable solution to the limitation of few data.

3 Methodology

3.1 Dataset

The Brain Tumor MRI dataset (Chakrabarty 2019), hosted on the Kaggle platform, contains 253 brain MRI images, of which 155 have tumors while 98 are normal images. Some of these images are illustrated in Figures 1 and 2. The main objective of this dataset is to predict brain tumors. Since the images vary in size, a standardization process was performed during preprocessing, adjusting all images to a uniform size of 256×256 pixels.

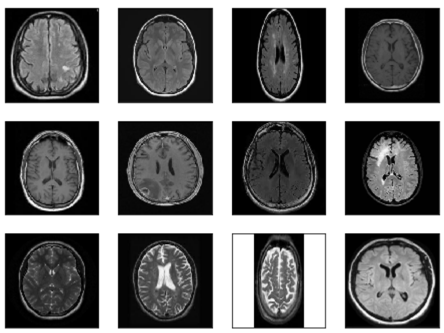

Figure 1: No tumor/normal images from the Brain Tumor MRI dataset.

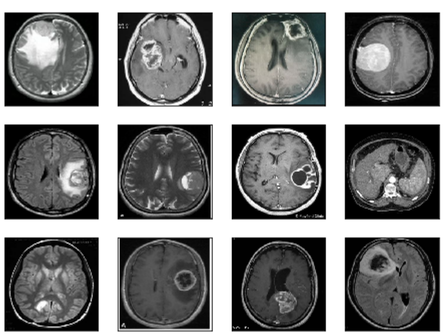

Figure 2: Tumor images from the Brain Tumor MRI dataset.

It was observed that most of the original images had unwanted borders, necessitating a step to remove these borders during preprocessing. Figure 3 illustrates this step, where the original image is cropped to eliminate the borders and then goes through a histogram equalization process to improve its quality.

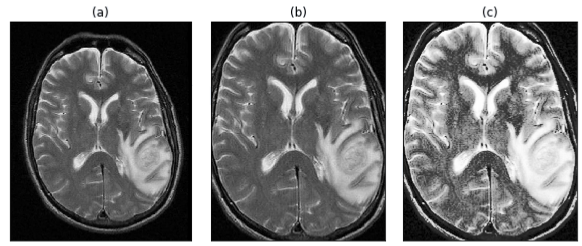

Figure 3: Pre-processing, where (a) is the original image, (b) is the cropped original image, and (c) is the final image through histogram equalization.

3.2 Model and Validation

Subsequently, a CNN was developed using transfer learning with the pre-trained VGG-16 model (Simonyan and Zisserman 2014). In this model, the input images are processed by VGG-16, where relevant features are extracted. These features are then flattened and passed to two fully connected layers, with the last one responsible for classifying the image as containing a tumor or not. The activation functions applied were Rectified Linear Unit (ReLU) and Sigmoid, with ReLU used in the first fully connected layer and Sigmoid applied in the second layer.

The ReLu function is widely used for Neural Network projects currently. The great advantage of using ReLU is that the activation of neurons is not done at the same time; if the input of some neurons is negative, they will not be activated, making the network efficient and faster. The ReLU function is given by

$$\varphi(u) = \max\{0, u\}, u \in \mathbb{R}.$$

This function returns the value of the input u if u is positive; otherwise, it returns 0. According to Nair and Hinton (2010), it is much easier to compute the input value as greater than or equal to 0. Still according to the authors, the optimization problem is smaller, as ReLU units result in a simpler cost function.

The Sigmoid or Logistic function is a non-linear link function that is used in Multilayer Perceptron. It is defined by

$$\varphi(u) = \frac{1}{1 + e^{-\alpha u}}, u \in \mathbb{R}, \alpha > 0$$

where α is the slope parameter of the Sigmoid function.

The validation method employed was Holdout, dividing the dataset into 70% for training, 15% for testing, and 15% for model validation. The Adadelta algorithm (Zeiler 2012) was selected for training the CNN, with the loss function being Cross-Entropy.

The Cross-Entropy for two categories is given by

$$L = -\left[y\log(p) + (1-y)\log(1-p)\right], 0 < p < 1,$$

where y represents the label (0 or 1), and p is the probability predicted by the model that the observation belongs to class 1.

In order to evaluate the transfer model used, Accuracy (ACC), Precision (P), Recall (R), and F1-score (F1) were used. These metrics are based on the confusion matrix (Table 1), where TP represents the true positives, TN the true negatives, FP the false positives, and FN the false negatives. They are defined as follows:

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}},$$

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}},$$

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \quad \text{and}$$

$$\mathrm{F1} = 2 \times \frac{\mathrm{P}\times\mathrm{R}}{\mathrm{P}+\mathrm{R}}.$$

Table 1: Structure of a 2 × 2 confusion matrix.

		True	
		No	Yes
Predicted	No	TN	FN
	Yes	FP	TP

Finally, a Streamlit application was created to classify brain X-ray images entered by the user, determining whether they present a malignant or benign tumor. The application analyzes images using CNNs and transfer learning techniques and provides results based on a pre-trained VGG-16 model.

4 Results

This work's Python codes are available at `https://github.com/FernandooMoraes/Article-brain-tumor`.

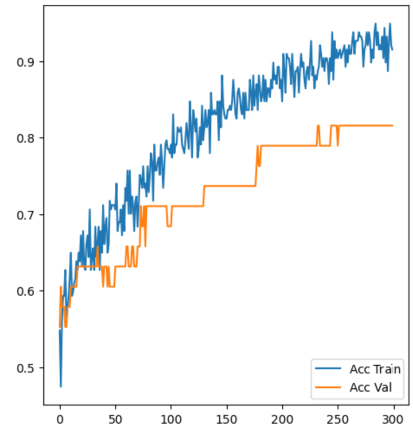

Figure 4: ACC performance.

After obtaining the model's prediction, a confusion matrix was constructed, presented in Table 2.

Table 2: Confusion matrix of the proposed model (test set).

		True	
		Normal	Tumor
Predicted	Normal	8	2
	Tumor	5	23

The analysis of Table 3 indicates that, despite having an ACC of approximately 82%, we achieved a P of 92%. A possible solution to improve these results would be to implement data augmentation techniques in the training set, such as the work of Mikołajczyk and Grochowski (2018). The performance graphs for ACC and the loss function are presented, respectively, in Figures 4 and 5, where it is evident that ACC increases over the epochs while the loss function decreases.

Table 3: Performance measures based on the confusion matrix (test set).

Measure	Value (%)
ACC	81.58
R	92.00
P	82.14
F1	86.79

The error rate of the proposed model is 6.65% on the training set, which is considered satisfactory, especially when compared to a random scenario, where the chance of correct predictions would be

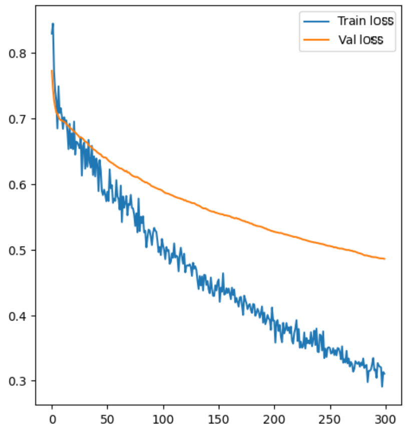

Figure 5: Loss function performance.

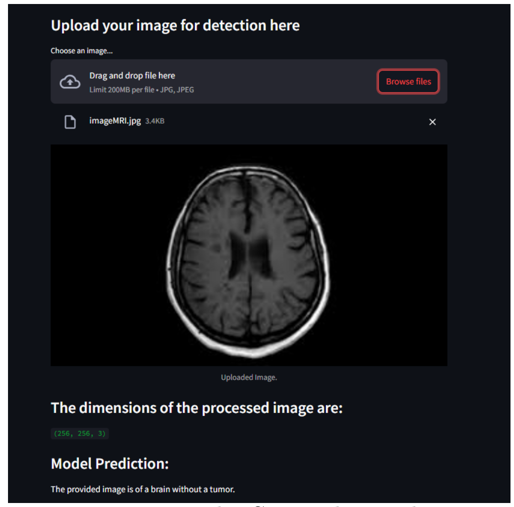

Figure 7: Using the Streamlit application.

50%. Additionally, compared to the work of Calas, Gutfilen, and Albuquerque Pereira (2012), the proposed model demonstrated a superior prediction rate compared to evaluations conducted by professionals with software.

The application developed in Streamlit classifies brain MRIs as containing tumors or not. Figure 6 shows the application's homepage, which includes a brief description of its functionalities. Figure 7 illustrates how the application works after loading an image, demonstrating the classification of the provided image without tumor. The application is available at the link: `https://brainapp.streamlit.app`.

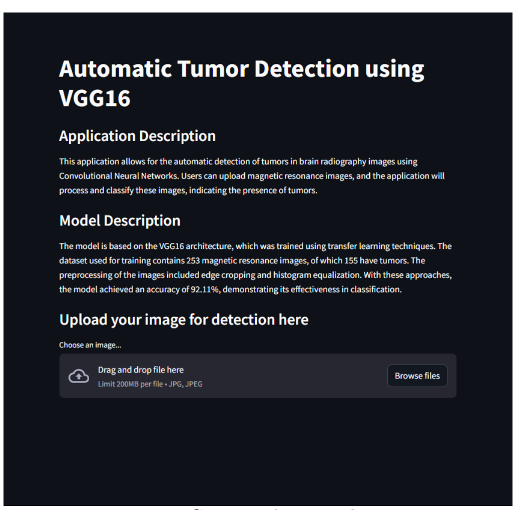

Figure 6: Streamlit application.

5 Final Remarks

This study aimed to train CNNs to classify brain X-ray images. The dataset used required a preprocessing step, which included cropping the edges of the images, inspired by the study of Saxena, Maheshwari, and Maheshwari (2019). Additionally, the images were enhanced through histogram equalization. A pre-trained model was chosen due to the limited number of images in the dataset, which is a recommended strategy to maximize training effectiveness.

The results were similar to those achieved by Saxena, Maheshwari, and Maheshwari (2019), who employed the same dataset in three transfer learning models: ResNet-50, Inception-V3, and VGG16. The authors reported an ACC of 90% with VGG-16, while the best-performing model achieved an ACC of 95%. It is worth noting that, as preprocessing, the authors only used cropping to adjust the edges. Another study that also applied transfer learning to this dataset was by Thotapally (2020), which obtained an ACC of 84% in the tests, exclusively using the cropping of the edges of the original images.

Although this study presented promising results in classifying brain X-ray images through CNNs and transfer learning, some limitations must be considered. The main limitation relates to the amount of data available in the dataset. The lack of images may compromise the model's generalization capability for new data, increasing the risk of overfitting. However, the findings of this study hold significant potential to inform and inspire future research in the field of medical imaging and machine learning, particularly in the development of more effective and robust models for brain X-ray image classification. Additionally, it is important to note that only one transfer learning model was used, which may limit the scope of the results.

There is significant potential for improvement based on the findings of this study. Expanding the dataset with additional sets found in the literature could lead to more robust and representative training. Adopting data augmentation techniques may also help improve the model's generalization. Exploring different transfer learning models could further enhance the model's performance. Finally, including other evaluation metrics will allow for a more comprehensive understanding of the model's performance, inspiring further research and development in this field.

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