Brain Tumor Classification Using Artificial Intelligence

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***Abstract*—The article explores the application of artificial intelligence, particularly convolutional neural networks (CNNs), in the classification of brain tumors. Starting with an overview of brain tumor classifications based on histopathological characteristics, genetic factors, and malignancy grading, the study delves into the methodology involving dataset acquisition, preprocessing, model architecture, and training. A dataset comprising 7023 images across four classes is utilized, with an 80-20 split for training and testing, respectively. The CNN-based model demonstrates robustness in classifying brain tumors, achieving a final accuracy of 99.09% and a validated accuracy of 92.07% on the testing set. The results showcase the model's proficiency, though the discussion section emphasizes the need for deeper analysis into misclassifications and the model's limited scope regarding tumor classifications. The article concludes by highlighting the potential of CNNs in medical image analysis and the challenges associated with incorporating a broader range of brain tumor classifications into the model.**

***Index Terms*—tumour, deep Learning, validation, aaccuracy, CNN, prediction**

I. Introduction

"In 2016, the World Health Organization updated its classification system for brain tumors, making a number of changes pertinent to radiologists, including the elimination or redefinition of previously recognized tumors, the addition of new tumors, and the incorporation of genetic factors into the definitions of infiltrating gliomas" [5].

The classification of primary brain tumors based on the primary cellular origin within the central nervous system (CNS) or its tissue, sometimes considering tumor location, serves as a standard practice. The determination of tumor malignancy or anaplasia is reliant on the histopathological characteristics observed. Due to the diverse nature and unique biology of CNS tumors, establishing a universally accepted histologic classification system has proven to be exceptionally challenging. Recent progress in comprehending the molecular biology of brain tumors, such as genomic modifications, significantly contributes to understanding tumor pathogenesis and plays a pivotal role in shaping tumor classification and grading [4]. Radiologists hold a crucial position in the diagnosis and management of brain tumors, necessitating their continual update with developments in the field to advance patient care and effectively collaborate with other healthcare providers.

The classifications are based on histopathological characteristics, cellular morphology, growth patterns, specific genetic abnormalities, and malignancy grading, understanding their biological behavior and prognosis [3].

A. Diffuse Astrocytic Tumors

- Astrocytomas (Grade II): These tumors exhibit a relatively low malignancy grade, characterized by a peak incidence between 25 and 50 years of age.
- Anaplastic Astrocytomas (Grade III): These are more malignant than Grade II astrocytomas. They display increased cellularity, cellular pleomorphism, distinct nuclear atypia, and exhibit higher mitotic activity. There's no spontaneous tumor necrosis or abnormal microvascular proliferation in these tumors.
- Glioblastomas (Grade IV): These are the most aggressive and malignant form. Glioblastomas exhibit characteristics like spontaneous tumor necrosis, pseudopalisading of tumor cells around necrotic areas, and florid endothelial proliferation.

B. Oligodendrogliomas

- Grade II (Oligodendrogliomas): These tumors originate mainly in the cerebral hemispheres of adults. They consist of moderately cellular, monomorphic tumor cells with round nuclei and often exhibit a "chicken-wire" pattern of capillaries.
- Grade III (Anaplastic Oligodendrogliomas): Anaplastic variants of oligodendrogliomas show increased nuclear pleomorphism, hypercellularity, brisk mitotic activity, microvascular proliferation, and spontaneous necrosis.

C. Meningiomas

- Malignancy Grade I: This is the most common form of meningiomas, which are usually solitary, lobulated tumors arising from the meninges. They typically displace but do not invade the adjacent brain or spinal cord.
- Atypical Meningiomas (Malignancy Grade II): These subtypes show more frequent recurrence and can exhibit aggressive behavior.
- Anaplastic Meningiomas (Malignancy Grade III): This is a less common, more aggressive form with aggressive histological features indicating higher malignancy.
- Meningeal Sarcomas (Malignancy Grade IV): These are highly malignant meningiomas.

Artificial neural network (ANN) is a flexible and powerful machine learning technique. However, it is under utilized in clinical medicine because of its technical challenges. ”Clinical diagnosis became one of the first areas to which the artificial neural network was applied. Acute myocardial infarction was one of the earliest applications but the range is wide, from appendicitis to the examination of biopsy specimens” [2].

The initial utilization of artificial neural networks for chest pain analysis emerged in 1989. In this study, a multilayer network was trained using data from 174 patients who presented with anterior chest pain. The network categorized patients into three diagnostic groups: high-risk cardiac, low-risk cardiac, and non-cardiac. However, these classifications lacked standardized criteria. Another application involved a retrospective analysis of 356 patients admitted to a cardiac intensive care unit, of which 120 had experienced a myocardial infarction. Using backpropagation, the network was trained on half of the patients with and without myocardial infarction and subsequently tested on the remaining patients, who were not part of the initial exposure to the network [2]. In the present, ANN are used in many fields due to their ability to learn complex patterns and relationships within data, making them valuable in various fields. Their capability to process large volumes of data, recognize intricate patterns, and adapt to changing inputs enables them to excel in tasks such as image and speech recognition, natural language processing, predictive analytics, and medical diagnosis.

II. Methodology

In this section, the dataset used for the research and the proposed approach of the classification is described.

A. *Dataset for Research*

The data collected using the application-based standard is the biggest challenge in machine learning. For this research, the dataset is taken from the website Kaggle. The dataset itself is a combination of three diferent datasets: figshare, SARTAJ dataset, and Br35H. The dataset consists of 7023 images divided in 4 classes as we can see in the next table.

Class	Test	Train	Total
Glioma	300	1321	1621
Meninglioma	306	1339	1645
Pituitary	300	1457	1757
No tumor	405	1595	2000

The proportion between the training and the test images has a proportion of aproximately 80 - 20. The 80% is used to train the model. During training, the model learns to recognize patterns and features within the images. It adjusts its parameters to make predictions based on the input data.

After training, you need to assess how well the model performs on new, unseen data. The remaining 20% of the images are used as a separate dataset (testing set) to evaluate the model’s performance. This set acts as a simulation of real-world scenarios where the model encounters new images it hasn’t seen before.

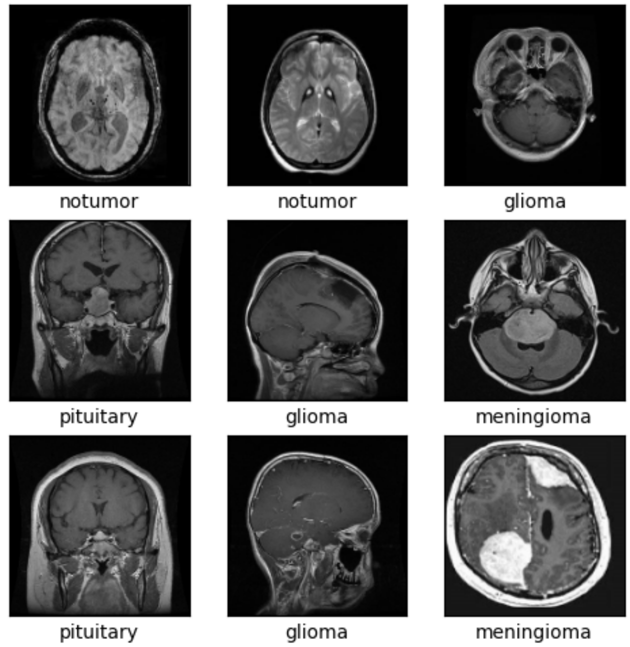


Fig. 1. Example of the samples of the dataset

B. *Proposed Method*

One of the largest limitations of traditional forms of artifitial neural networks is that they tend to struggle with the computational complexity required to compute image data. Recently, the advancement of *convolutional neural network* has been developed by many researchers to solve computer vision problems more precisely and in a short time. In convolutional neural networks (CNNs), every neuron continues to take in an input and execute an operation, which forms the fundamental principle shared by numerous artificial neural networks (ANNs). Starting from the initial raw image vectors to the ultimate output representing the class score, the entirety of the network will continue to represent a unified perceptive score function. The final layer will encompass loss functions linked to the different classes.

”The only notable difference between CNNs and traditional ANNs is that CNNs are primarily used in the field of pattern recognition within images. This allows us to encode image-specific features into the architecture, making the network more suited for image-focused tasks - whilst further reducing the parameters required to set up the model”.

The structure of the full convolution neural network is described in Figure 2.

The implementation of deep learning mechanisms has various modules and forms. The proposed method involves a supervised learning class of neural networks. The model is feeded with the images and it´s corresponding label.

C. *Preprocessing of the Data*

The images from the dataset has different sizes from each other (aproximately 500x500 each) so the first step to process the images is to resized them into one size only. In this case,

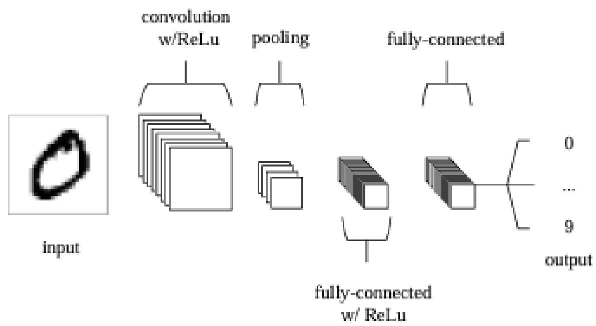


Fig. 2. Simple CNN architecture composed of just five layers

because of the amount of images and to reduce training time, the images were resized to 250x250 pixels. Then, in order to adapt the data to fit correctly in the proposed model, it is necessary to normalize the pixel values. It helps in achieving better convergence and stability during the training process of neural networks. Pixel values typically are in range from 0 to 255 in images. Dividing by 255 scales these values to fall within the range of 0 to 1. This normalization is achieved by ensuring that the pixel values are now between 0 and 1.

D. Structure and Training of the Model

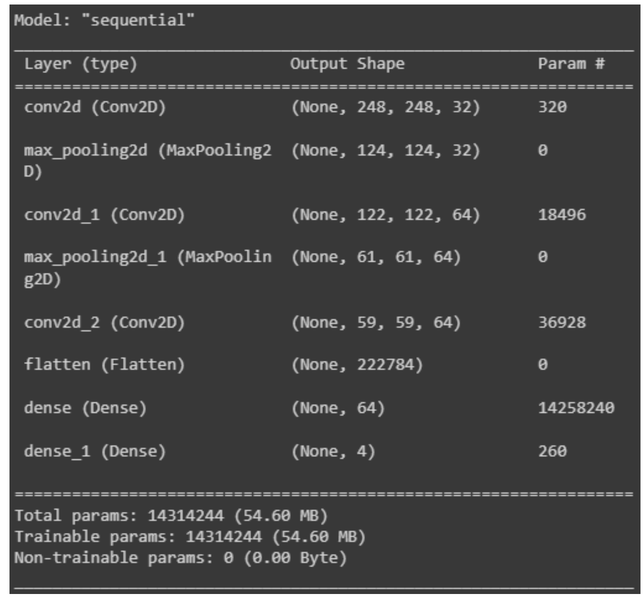
In this section, the number of convolutional and learning layers are established for the model to learn and train correctly. For the convolutional part, is needed a convolutional layer accompanied with a max pooling layer. For the convolutional part of the model the *ReLu* function is used. The upper hand of using ReLU function is that all the neurons are not activated at the same time. This implies that a neuron will be deactivated only when the output of linear transformation is zero. For the learning part, a ReLu funtion is used as well for the hidden layer. In the output layer, the number of classes must be specified and a *softmax* funtion is used to a better visualization of the results. The softmax function unlike sigmoid functions which are used for binary classification, can be used for multiclass classification problems. The function, for every data point of all the individual classes, returns the probability.

A summary of the final model is represented in figure 3 where the total amount of parameters is visible.

The optimizer is a crucial component of the neural network responsible for updating the model's weights during training to minimize the loss function. The Adam optimizer used is known for its efficiency and ability to handle large datasets and models with high dimensionality.

III. Results

After the training of the CNN, the model has a final accuracy of 0.9909 and a loss of 0.0316. Along with this value, the model developed a validation of both values with the separated dataset of the testing images. The final validated accuracy is 0.9207. The figure 4 shows a accuracy vs. validated accuracy graphic along the 10 epochs that the model realized during it´s training.



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 248, 248, 32)      320

 max_pooling2d (MaxPooling2  (None, 124, 124, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 122, 122, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 61, 61, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 59, 59, 64)        36928

 flatten (Flatten)           (None, 222784)            0

 dense (Dense)               (None, 64)                14258240

 dense_1 (Dense)             (None, 4)                 260

=================================================================
Total params: 14314244 (54.60 MB)
Trainable params: 14314244 (54.60 MB)
Non-trainable params: 0 (0.00 Byte)
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Fig. 3. Summary of the model

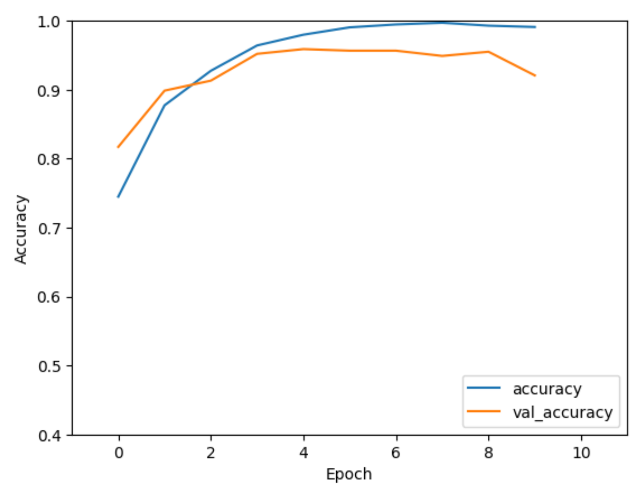

Fig. 4. Accuracy graphic of the model

In figure 5, a representation of the outputs of the model depending on the image given. Each image shows the classification prediction and in parenthesis the real label given in the dataset. Along with the prediction, the model brings a graphic with the probability of each class, using the results obtained by the softmax function, and highlighting the biggest one.

GitHub repository: Brain tumor classification model.

IV. Discussion

An accuracy of 92% in a classification model can indeed be perceived as commendable, particularly within the context of medical image analysis. However, within the domain of medical diagnostics, precision and reliability are paramount, demanding the pursuit of even higher accuracies for practical clinical applications. Despite achieving a 92% accuracy in classifying brain tumor images, it's crucial to acknowledge

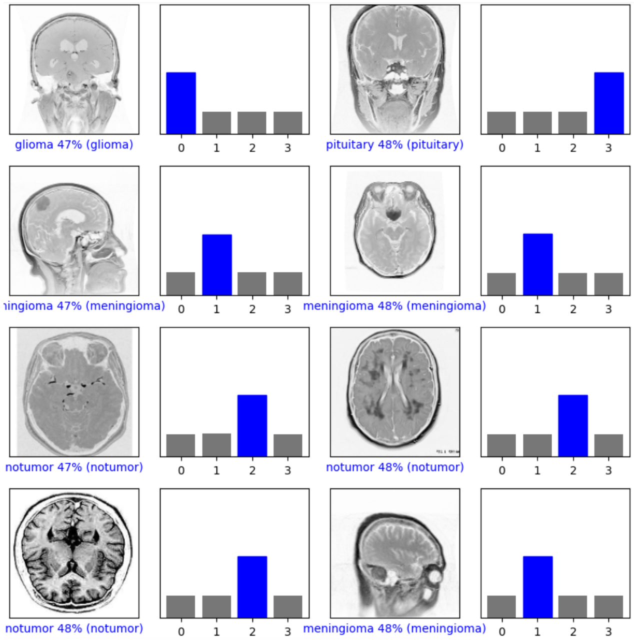

Fig. 5. Classification of 8 MRI according to the model

the potential variability in significance across different medical scenarios.

The high accuracy obtained on the testing set underscores the model's proficiency in discerning brain tumor patterns from medical imaging data. However, to ensure clinical applicability, a deeper exploration into misclassifications or instances of uncertainty is imperative. The medical field demands not only high accuracy but also a thorough understanding of the model's limitations and potential sources of error.

While the implemented CNN demonstrates its rapid and effective classification ability, it's essential to acknowledge the limitations of the model's classification scope. This model, focusing on three tumor classifications while excluding the 'no tumor' category, offers a streamlined approach. However, comprehensive brain tumor diagnosis often involves a wider spectrum of classifications, as outlined in the introduction. Integrating additional categories into the model would necessitate a more complex dataset, potentially posing challenges in data collection due to the intricacies involved in obtaining diverse and accurately labeled medical images.

Furthermore, the advantage of employing CNNs lies in their ability to identify intricate patterns within images that might elude human perception. Expanding the model's scope to encompass a broader range of brain tumor classifications would undoubtedly require meticulous data curation and potentially more advanced CNN architectures or transfer learning techniques.

V. Conclusion

The study has provided valuable insights into the efficacy of convolutional neural networks (CNNs) in brain tumor classification. Achieving a final accuracy of 99.09% and a validated accuracy of 92.07% on the testing dataset underscores the model's competence in discerning brain tumor patterns from medical imaging data. However, the discussion emphasizes the necessity for a more in-depth exploration of misclassifications and uncertainties, essential for ensuring clinical applicability and understanding the model's limitations.

While the implemented CNN demonstrates swift and accurate classification capabilities, its scope is limited to three tumor classifications, excluding the 'no tumor' category. Recognizing the need for a more comprehensive approach in brain tumor diagnosis, the article acknowledges the challenges associated with integrating additional tumor categories into the model. Expanding the model's scope would demand meticulous data curation and potentially more sophisticated CNN architectures or transfer learning techniques.

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