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Research Article

Convolutional Neural Network (CNN) Prediction on Meningioma, Glioma with Tensorflow

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Abstract:

Brain tumors can significantly affect a patient's life in a variety of ways. Classification of brain tumors is also important. Artificial intelligence (AI) techniques such as machine learning and deep learning can be very beneficial to physicians to classify tumors based on various parameters. In this study, the dataset is comprised of two distinct components which were prepared specifically for testing and training purposes, respectively. TensorFlow software library was used to utilize of Convolutional Neural Network (CNN). Since the most suitable weight values to solve the problem in deep learning are calculated step by step, the performance in the first epochs was low and unstable compared to the progressive values, and the performance increased as the number of epochs increased. However, after a certain step, the learning status of our model decreased considerably. The accuracy of the created model was observed to reach 0,90. As a result, as stated in its intended use, a mechanism that helps physicians and uses time efficiently has been successfully developed.

1. Introduction

Brain tumors are abnormal growths of cells in the brain or surrounding tissues. Brain tumors can significantly impact a patient's life in various ways, depending on the type, size, and location of the tumor, as well as the individual's overall health and other factors. Some common effects of brain tumors on a patient's life may include headaches, seizures, cognitive and memory problems, speech difficulties, vision and hearing changes, fatigue, and emotional or psychological distress. Treatment options such as surgery, radiation therapy, chemotherapy, and supportive care may also have their own effects and impact on the patient's quality of life [1]. According to the American Brain Tumor Association, it is estimated that over 87,000 people in the United States will be diagnosed with a primary brain tumor in 2022 [2].

Diagnosis of a brain tumor typically involves imaging tests such as MRI or CT scans, followed by a biopsy or other tests to determine the type and grade of the tumor. Furthermore, classification of brain tumors is also important for several reasons. Firstly, it helps to determine the type and grade of the tumor, which can guide treatment decisions and prognosis. Secondly, it allows for more accurate and consistent diagnosis, which can help improve patient outcomes. Thirdly, classification can aid in the development of personalized treatment plans and targeted therapies. Finally, it enables researchers to study and better understand the biology and behavior of different types of brain tumors, which could lead to the development of new treatments and improved patient care [3,4].

Artificial intelligence (AI) techniques such as machine learning and deep learning can be used to classify tumors based on various parameters such as tumor size, shape, texture, and other features extracted from medical images or clinical data.

One common approach is to use convolutional neural networks (CNNs), a type of deep learning algorithm that has been shown to be highly effective in image classification tasks. CNNs can be trained on large datasets of medical images such as CT scans, MRIs, or mammograms, to learn to distinguish between different types of tumors based on their features.

Another approach is to use decision trees or support vector machines (SVMs) to classify tumors based on clinical data such as patient demographics, medical history, and lab results. These algorithms can learn to identify patterns and correlations between different factors and predict the likelihood of a tumor being malignant or benign. AI-based tumor classification systems can provide doctors with valuable insights into the nature and severity of tumors, helping them to make more informed decisions about treatment options and improve patient outcomes. However, it is important to note that AI should be used as a complementary tool to human expertise and not as a replacement for it. Doctors should always make the final decision based on their clinical judgment and experience.

There are some potential disadvantages to physicians classifying brain tumors on their own without any AI algorithm which help physicians to distinguish. Here are a few examples:

- Misdiagnosis
- Treatment variability
- Lack of standardization
- Limited predictive value

It is important for physicians to carefully consider all available information when classifying brain tumors and to use classification systems as tools to guide treatment decisions, rather than relying solely on them.

Misdiagnosis: Brain tumors can be challenging to diagnose because symptoms can vary widely, and different types of tumors may appear similar on imaging tests. If a physician relies too heavily on a particular classification system, they may misdiagnose a tumor or overlook important features that could affect treatment decisions. A study published in the Journal of Neurosurgery found that the accuracy of brain tumor diagnosis varied widely among physicians, with some cases being misdiagnosed as much as 40% of the time [5]. This highlights the potential risk of misdiagnosis, particularly when relying solely on classification systems. Treatment variability: Different types of brain tumors may require different treatments, and misclassification can result in inappropriate treatment decisions.

A study published in the Journal of Neuro-Oncology found that incorrect classification of gliomas led to inappropriate treatment decisions in nearly 20% of cases [6]. Lack of standardization: There are several different classification systems for brain tumors, and different physicians may use different criteria or terminology. This can make it challenging to compare research findings or treatment outcomes across different studies or institutions. A review article in the Journal of Neuropathology and Experimental Neurology notes that the World Health Organization's classification system for brain tumors has undergone several revisions, which can make it difficult to compare data across studies [7]. Limited predictive value: While classification systems can be helpful in guiding treatment decisions, they are not always predictive of patient outcomes. A study published in the Journal of Clinical Oncology found that histological classification of gliomas had limited prognostic value, with clinical factors such as age and performance status being more predictive of survival [8]. The three specific types of tumors studied in this article are pituitary tumor, malignant tumor, and meningioma tumor. Pituitary tumor is the mass formation as a result of uncontrolled division of the cells forming the pituitary gland tissue for some reasons; It is called a pituitary adenoma. This tumor type represents 12% of all tumors [9]. Most pituitary tumors are benign tumors that do not spread beyond the skull. Even if these tumors are not considered cancerous, it is inconvenient to leave them there without intervention, as their location is close to the brain and can affect the hormonal level of the body. Malignant tumors, on the other hand, are considered cancerous and they become life-threatening by metastasizing in the area where they are located. Examination and prompt initiation of treatment are very important. Meningioma tumors are slow-growing and mostly benign tumors that surround the meninges and constitute 15-20% of all intracranial tumors and are seen at a higher rate in women than in men [10].

2. Material and Methods

In this study, the dataset utilized was procured through a search conducted on the Kaggle platform [11]. The dataset is comprised of two distinct components which were prepared specifically for testing and training purposes, respectively. Each of these sections comprises a total of 3264 Magnetic Resonance Imaging (MRI) images encompassing three different tumor types, namely meningioma (fig 1), glioma (fig 2) and pituitary tumors, alongside tumor-free subcategories. This dataset contains 394 MR images for testing and 2870 MR images for training (Table 1). The tabulated information below presents the distribution of MR images across various categories, including tumor-free images, glioma tumors, meningioma tumors, and pituitary tumors.

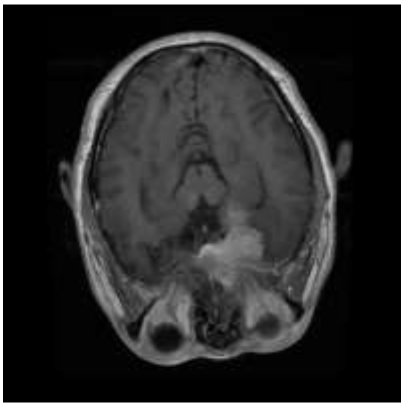

Figure 1. *MR Image with Meningioma Tumor*

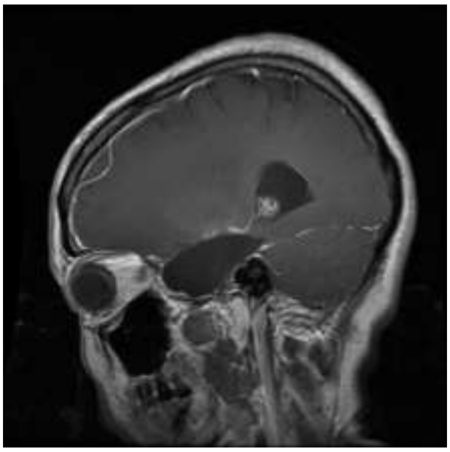

Figure 2: *MR Image with Glioma Tumor*

***Table 1**. Distribution of MR images*

MR Images	Testing	Training
Tumor-free	105	395
Glioma tumors	100	826
Meningioma tumors	115	822
Pituitary tumors	74	827

In the field of machine learning, neural networks have shown remarkable success in a wide range of areas such as computer vision[12], natural language processing[13], and bioinformatics[14]. These models also have enormous potential to promote data analysis and modeling for various problems in educational and behavioral sciences given their flexibility and scalability as universal function approximator[15]. The Convolutional Neural Network (CNN) operates on a mechanism inspired by the functioning of neurons in the human brain. It is a deep learning algorithm that has proven to be highly effective in various computer vision tasks, including image classification, object detection, and image segmentation. (fig 3) The underlying principles of CNN involve the extraction and analysis of hierarchical features from input images, allowing for accurate identification and understanding of the visual content.

CNN learns by comparing and contrasting the unique properties and patterns present within the input data. When presented with images, it aims to discern and differentiate various objects or classes by leveraging the spatial relationships and local correlations present in the data.

This process of feature extraction occurs through the utilization of convolutional layers and filters (fig 4) within the CNN architecture. These layers perform convolution operations on the input images, capturing local information and detecting low-level

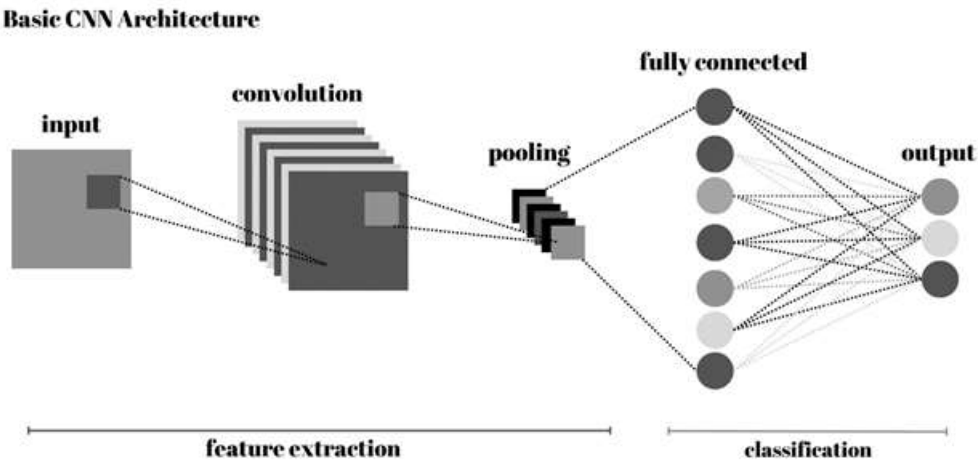

Figure 3. *Basic CNN Architecture*

features such as curves, edges, and textures. By incorporating multiple layers, CNN can hierarchically learn more complex and abstract representations, combining the detected low-level features to form higher-level concepts. Furthermore, CNN employs pooling layers to downsample the extracted features, reducing the dimensionality of the representations while retaining the most salient information. This enables the network to focus on important features and discard redundant or less informative details. Additionally, the activation functions applied after each convolutional or pooling layer introduce non-linearities, facilitating the network's ability to capture and model complex relationships between features. By iteratively training on a large labeled dataset, CNN learns to optimize its internal parameters (weights and biases) through a process known as backpropagation. Backpropagation involves the computation of gradients, which are used to update the network's parameters based on the error between the predicted output and the ground truth labels. This iterative training process allows CNN to gradually refine its feature representations, improving its ability to accurately classify and recognize objects in new, unseen images. In summary, the Convolutional Neural Network (CNN) paradigm draws inspiration from the biological structure and functioning of the human brain. Through the extraction of hierarchical features and the application of convolution, pooling, and activation operations, CNN effectively learns to distinguish and classify objects within images. The iterative training process further enhances its performance by optimizing the network's internal parameters. As a result, CNN has emerged as a powerful tool in computer vision, enabling a wide range of applications in fields such as medical imaging, autonomous driving, and image understanding. In our study, the Python programming language was used to implement our algorithm, given its versatility and extensive support within the data science community. Also we aim to harness the potential of Convolutional Neural Network (CNN) methodology (fig 4). To accomplish this, we utilized the TensorFlow software library, developed by the Google Brain Team, which stands as a popular choice for artificial intelligence and machine learning. TensorFlow is a flexible and scalable software library for numerical computations using dataflow graphs. It is a powerful tool that helps in the rapid and efficient development of projects in the field of artificial intelligence and deep learning, providing many functions and tools for building and training neural networks that are widely used in deep learning projects; and it is also compatible with Python language and has a large ecosystem. This library and related tools enable users to efficiently program and train neural network and other machine learning models and deploy them to production. TensorFlow operates using multidimensional arrays called tensors. These tensors allow Python to complete more complicated computations that are needed when working with machine learning. This format of holding information is used to save much more complicated information in a tensor than in a typical one dimensional array [16]. It provides high performance computing by effectively using hardware accelerators such as GPU (Graphics Processing Unit) and TPU (Tensor Processing Unit). It offers optimization techniques to accelerate large-scale data processing and training processes.

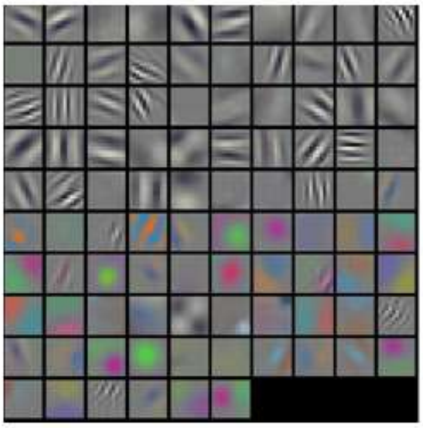

Figure 4. *Example of some of filters used in CNN*

In our approach, we embarked on a multi-step process to effectively leverage the CNN architecture. Initially, we focused on the "Training" section of the dataset, containing MRI images, and performed a classification task. The goal was to categorize the images into four distinct groups: non-tumor, meningioma tumor, malignant tumor, and pituitary tumor. By organizing the data in this manner, we established a foundation for the subsequent steps of our algorithm. To facilitate the learning process, we associated the MRI images from each tumor type with their corresponding labeled folders. This step involved providing the artificial intelligence model with a dedicated set of images for each tumor category, thereby enabling it to learn and recognize the unique visual features associated with each specific tumor type. Through the application of the CNN methodology, the model underwent a series of data processing operations, including convolution and pooling, to extract meaningful patterns and distinctive characteristics from the input images. As the model iteratively processed and analyzed the images, it gradually acquired the ability to discriminate and differentiate between the different tumor types based on their visual attributes. By undertaking numerous repetitions and combinations, the model honed its capacity to learn and accurately identify the presence of a specific tumor type within an individual MRI image. This training process was crucial in enabling the CNN model to progressively enhance its discriminatory capabilities. The model's ability to recognize subtle variations and intricate patterns within the images improved with each iteration. As the CNN architecture learned to extract and associate low-level features, such as edges and curves, it gradually built more abstract and higher-level representations of the tumor types present in the images. This hierarchical learning allowed the model to capture increasingly complex relationships between features, leading to more accurate classification outcomes.

In summary, our study leveraged the CNN methodology through the TensorFlow software library to train an artificial intelligence model for the classification of MRI images. The iterative learning process, aided by the CNN architecture, enabled the model to discern and identify the unique features associated with different tumor types. By processing and analyzing the images repetitively, the model acquired the ability to make accurate tumor type classifications based on the distinctive visual patterns observed within the input data. After that, we designated a separate set of images for testing purposes to evaluate the performance of the trained artificial intelligence model and further improve the accuracy of its predictions. By explicitly associating each test image with its corresponding tumor type, we enabled the model to conduct a comparative analysis based on its acquired knowledge and reference information.

In this evaluation phase, the artificial intelligence model first leveraged its learned representations to assess the test images against the previously encountered tumor types. By scrutinizing the distinctive features extracted from the test images, the model made comparisons with the established reference information. Through repeated iterations of this comparative process, the model progressively refined its ability to discern and differentiate the characteristic traits of the various tumor types, ultimately leading to a higher accuracy rate.

By engaging in this iterative evaluation and refinement cycle, the artificial intelligence model further fine-tuned its discriminatory capabilities. The repetitive exposure to diverse test images allowed the model to strengthen its understanding of the subtle visual cues specific to each tumor type, resulting in heightened accuracy when predicting the tumor type of an unseen image.

3. Results

Our study employed a distinct set of test images to assess the performance of the trained artificial intelligence model. Through iterative comparisons with learned representations and reference information, the model refined its ability to differentiate between tumor types. This iterative process contributed to achieving a higher accuracy rate by enhancing the model's capacity to recognize and discern the unique characteristics associated with different tumor types (fig 5).

The model was trained with the training set and the weights were updated again. This process was repeated at each training step to calculate the most appropriate weight values for the model. Each of these training steps is called an “epoch”.

While the model is being trained, not all of the data are included in the training at the same time. They take part in education in a certain number of parts. The first piece is trained, the performance of the model is tested, and the weights are updated according to the success with backpropagation. Then the model is retrained with the new training set and the weights are updated again.

Since the most suitable weight values to solve the problem in deep learning are calculated step by step, the performance in the first epochs was low and unstable compared to the progressive values, and the performance increased as the number of epochs increased. However, after a certain step, the learning status of our model decreased considerably.

The accuracy, macro average and weighted average values for all tumor types are shown below as 0 refers to Glioma Tumor, 1 refers to No Tumor, 2 refers to Meningioma Tumor and 3 refers to Pituitary Tumor (fig 6). Finally, the values obtained for each training round (epoch) are given in the Fig 7.

4. Conclusions

In this study, a mechanism that can help physicians in the classification of glioma, meningioma and pituitary gland tumors, which are the three most common types of brain tumors, and that uses time efficiently has been studied. It is aimed to examine the brain cross-section images obtained by using an MRI device, to understand which type of brain tumor it corresponds to, and thus to diagnose the patient's condition correctly and in the shortest possible time, and to start the treatment as soon as possible. In addition, it was aimed to expand the size of this study by adding a tumor-free image class. It has been prioritized that the obtained classification mechanism has a high accuracy rate. For these purposes, a CNN model was created with TensorFlow and the model was evaluated by considering the success rate on the basis of various parameters. As a result of the examinations, it was determined that the accuracy rate of the model created was close to 0.90 and slightly above. As stated in the aim of the study, a mechanism that helps physicians and uses time efficiently has been successfully developed. When other studies are examined, it is seen that the accuracy rate obtained is quite close to some successful studies. Due to the fact that the study is open to development, more efficient results can be obtained in the future. For this, the data set used in the study can be expanded to ensure that the learning models work more effectively. After the data set is enlarged, the cross-section images can be grouped based on various desired criteria and the models can be trained in this way, and the effect on the classification result can be observed.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.

```
- val_accuracy: 0.8469
- val_accuracy: 0.9320
- val_accuracy: 0.9150
- val_accuracy: 0.9150
- val_accuracy: 0.8878
- val_accuracy: 0.8980
- val_accuracy: 0.9320
- val_accuracy: 0.8810
- val_accuracy: 0.9116
- val_accuracy: 0.9354
- val_accuracy: 0.9524
- val_accuracy: 0.9592
```

Figure 5. *Accuracy Outputs*

	precision	recall	f1-score	support
0	0.91	0.94	0.92	93
1	0.98	0.84	0.91	51
2	0.92	0.98	0.95	96
3	1.00	0.98	0.99	87
accuracy			0.94	327
macro avg	0.95	0.93	0.94	327
weighted avg	0.95	0.94	0.94	327

Figure 6. *Accuracy, Macro Avg. and Weighted Avg. Values*

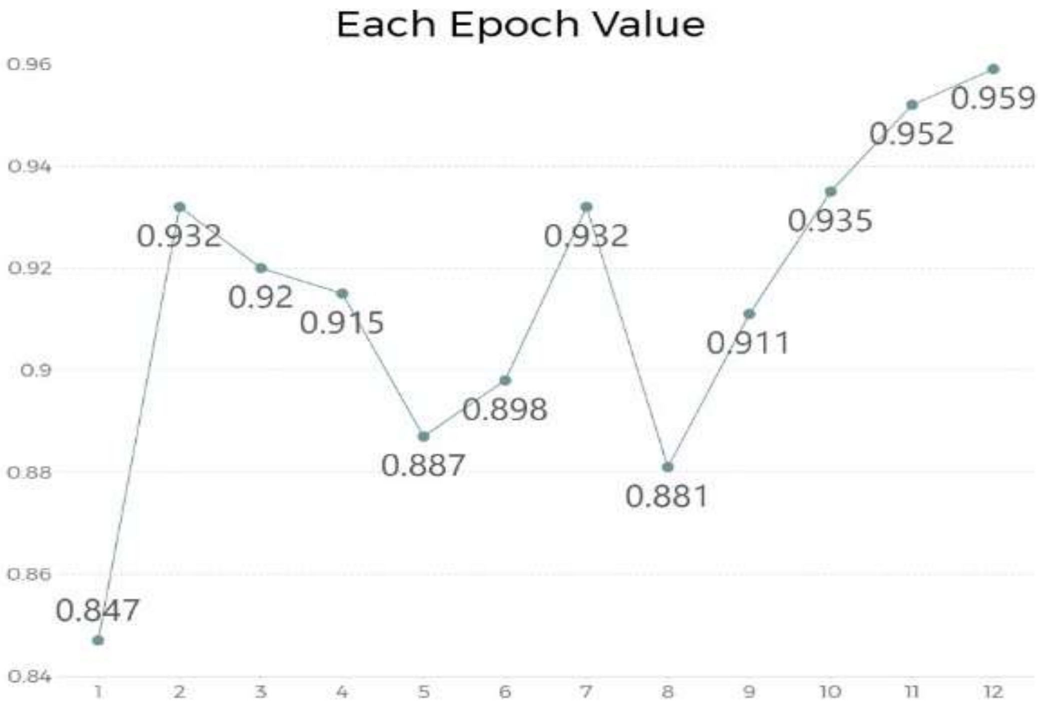

Figure 7. *Each Epoch Value*

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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