The Usage of Convolutional Neural Networks to Classify Brain Tumors in MRIs

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Abstract

Data was taken and put into a CNN model in which a diagnosis was predicted with ~95% accuracy.
The Usage of Convolutional Neural Networks to Classify Brain Tumors in MRIs

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ABSTRACT Indisputably, brain tumors are an exceedingly prevalent affliction, impacting millions throughout the world. Regrettably, contemporary brain tumor detection methods suffer from the significant drawbacks of being slow, requiring professionals, and being time-consuming, thus diminishing the prospects of survival for afflicted patients. In light of these challenges, there is an urgent need for innovative solutions that can revolutionize brain tumor detection, diagnosis, and treatment. In this paper, I present an accurate, fast, and automated way of diagnosing brain tumors using a convolutional neural network (CNN). My method uses magnetic resonance imaging (MRIs) of potential brain tumors and classifies them as either glioma tumor, meningioma tumor, pituitary tumor, or no tumor using a convolutional neural network (CNN). My model showed approximately 95% accuracy in diagnosing these tumors when averaged using the final 20% of samples. The high accuracy proves that machine learning can be used as an effective way to clinically diagnose brain tumors.

INDEX TERMS MRI, Brain, Machine Learning, Convolutional Neural Network

I. INTRODUCTION
In 2023 alone, 94,390 Americans will receive a primary tumor diagnosis [1]. For all patients with a malignant brain tumor, the relative survival rate is 35.7%, meaning that a total of 18,990 Americans will die of brain tumors in 2023 alone [1]. For one tumor, glioblastoma multiforme, the five-year survival rate for a patient over the age of 40 is a mere 6% [2]. For those who do not receive treatment for glioblastoma, the life expectancy is a mere four months while for those who do receive treatment, these four months can be turned into over 15 months [3]. Thus, it is absolutely vital that we are able to diagnose those with brain tumors as early as possible in order to increase survival rates and time. However, according to a recent study which included 330 pediatric brain tumor patients, the mean time to diagnose was 7.7 months, meaning that from onset of the first visit to the doctor, it takes 7.7 months to properly diagnose the patient [4]. The main cause of this delay is system delay, which is when the healthcare system delays procedures ultimately delaying the diagnosis [5]. It is crucial for the medical system to decrease this system delay because this can lead to larger tumors, which decreases life expectancy [5].

There are several ways to diagnose a brain tumor. Traditional methods include magnetic resonance imaging (MRI), biopsy, computed tomography (CT) scan, positron emission tomography (PET) scan, and biomarker testing (6). An MRI creates images of the brain using magnetic fields, a biopsy takes a sample of the suspected tumor to make a diagnosis, a CT scan takes pictures of the brain...
using x-rays, a PET scan uses radioactive substances to determine if there are tumor cells, and biomarker testing uses laboratory tests on tumor samples to identify specific biomarkers that are known to be tumors [6]. However, a flaw to all these tests is that doctors and other professionals must manually look at the results to determine if there is a tumor, which significantly increases the system delay. In addition to needing professionals to determine the results of these tests, professionals are also needed to conduct these tests. To aid in decreasing this delay, I wish to use a convolutional neural network (CNN) to help classify brain MRI data. This model would be fully automated. First, the image would be fed to the CNN and the Convolutional and Pooling layers would recognize patterns to classify the image. After these inputs, I would test using previously unseen data to determine the accuracy of the model.

My primary objective is to investigate the feasibility of employing a convolutional neural network for precise brain tumor detection through the analysis of MRI images. Furthermore, I endeavor to ascertain the extent to which convolutional neural networks can reliably predict the presence of brain tumors. My hypothesis posits that CNNs can achieve a commendable level of accuracy in brain tumor detection. To derive my findings, I rigorously assessed my CNN model using 2400 MRI images and computed the average accuracy based on the latter 20% of the samples. These results unequivocally demonstrated that the CNN model achieved a mean accuracy of approximately 95%. Consequently, my findings underscore the robustness of CNNs as a diagnostic tool for brain tumors, showcasing their potential applicability in clinical settings.

II. METHODOLOGY

In my study, I constructed a Convolutional Neural Network (CNN) with a specific architecture to analyze images. The CNN consisted of various types of layers that played crucial roles in understanding the image content and making predictions. The core of my CNN comprised four Convolutional layers and four Pooling layers. These layers helped in extracting important features from the input images. The first Convolutional layer, Conv2D, was responsible for processing the images. It used 32 filters, each having a size of 3 x 3. The activation function used here was Rectified Linear Activation (ReLU), which introduced non-linearity to the model. The images fed into this layer needed to have dimensions of 300 x 300 pixels, and being in the RGB color model, they were three-dimensional. Following each Conv2D layer, I utilized the MaxPooling2D layer, which reduced the spatial dimensions of the output by taking the maximum values from a 2 x 2 pooling window. This pooling process helped in retaining important features while reducing the computational load. I then repeated a similar pattern of Convolutional and Pooling layers four times, each time adjusting the number of filters and the spatial dimensions. Layer three employed another Conv2D operation with 64 filters, while layer four performed pooling to further downsize the output from layer three. This pattern continued with layer five using 128 filters in the Conv2D operation, and layer six performing another MaxPooling2D. Finally, layer seven used 256 filters in the Conv2D operation, and layer eight performed pooling. Throughout these layers, the number of filters increased progressively in the Convolutional layers. This step was strategic to enable the neural network to learn and abstract more complex features as the image data propagated through the network. The layers acted as feature extractors, with deeper layers capturing more intricate details. After the Convolutional and Pooling layers, I introduced two Dense layers. The first Dense layer, which had Rectified Linear Activation (ReLU), was designed to enhance non-linearities in the model. The second Dense layer employed a sigmoid activation function. These Dense layers played a role in classifying images based on the features learned during the earlier layers. To summarize, my CNN architecture was carefully designed with Convolutional and Pooling layers to extract image features progressively. The deeper layers captured higher-level abstractions. The Dense layers at the end performed image classification based on these features. Finally, I compiled the model and outputted the results.

III. RESULTS

My project focused on the development of a Convolutional Neural Network (CNN) for brain tumor detection using MRI scans (Fig. 1, Fig. 2). I used M. Hossein Hashemi’s "Crystal Clean: Brain Tumors MRI Dataset" to provide us with over 21,000 MRIs to work with, out of which 12,000 were chosen [7]. Out of these 12,000 MRIs, 7200 MRIs (60%) were placed in the training category, 2400 MRIs (20%) were placed in the validation category, and 2400 (20%) MRIs were placed in the testing category (Table 1). I tested my CNN with a total of 50 epochs, with each epoch representing one complete iteration through the training dataset.

At the outset, in the initial epoch, my model achieved an accuracy of 61.61%. As the model continued its learning process, it steadily improved its accuracy, demonstrating consistent progress (Fig. 3). By the 7th epoch, a pivotal milestone was reached with an accuracy of 80.90%, marking the first instance of surpassing 80% accuracy. Subsequently, the model's performance became increasingly refined. In epochs 11 through 20, it continued to enhance its accuracy, consistently exceeding the 85% mark. The trend of improvement persisted throughout the training process. In epochs 21 to 30, the model's accuracy surpassed 90%, showcasing its capability to make precise predictions. Towards the latter stages of training, the model maintained a high level of accuracy, even as it approached the 50th epoch. The model's overall mean accuracy over the final 20 epochs culminated at an exceptional 94.69%. This remarkable accuracy progression underscores the efficacy of my CNN-based brain tumor detection system, signifying its potential.
value in clinical applications and medical imaging. Further refinements and optimizations could potentially enhance its performance and broader utility in real-world healthcare scenarios.

IV. DISCUSSION
In my study, I rigorously assessed the performance of a Convolutional Neural Network (CNN) for the detection of brain tumors using MRI images over 50 epochs. I utilized a dataset of 2400 MRI images, with the CNN model achieving a remarkable mean accuracy of approximately 95% over the final 20 epochs. The initial epoch's accuracy was 61.61%, steadily improving as the model continued its learning process. By the 7th epoch, it surpassed 80% accuracy, and in epochs 11 through 20, it consistently exceeded 85%. The model's accuracy surpassed 90% in epochs 21 to 30, highlighting its potential for high-precision diagnostic applications. The overall mean accuracy over the final 20 epochs was 94.69%.

My results underscore the potential significance of CNNs in automating brain tumor detection, particularly from MRI images. However, it is important to consider certain factors and limitations that could have influenced my results. Firstly, the size of my dataset, though substantial, might benefit from even larger and more diverse datasets to further validate the model's performance across various patient populations and clinical settings. Additionally, while I achieved a high level of accuracy, future research could explore different architectures and hyperparameters to optimize the model further. Moreover, the model's performance might vary when faced with different types and stages of brain tumors, and future experiments could focus on these variations for a more nuanced understanding.

The significance of my results lies in the potential impact on healthcare. Automating brain tumor detection with high accuracy through CNNs can significantly reduce the system delay currently present in healthcare, leading to earlier diagnoses and interventions. This, in turn, can potentially improve patient outcomes, especially for conditions like glioblastoma multiforme, where time is of the essence. While my CNN model demonstrates excellent performance in detecting tumors in MRI images, its real-world applicability and integration into clinical practice require further validation.

Remaining scientific questions and potential future experiments revolve around the robustness and adaptability of the CNN model. Researchers could explore how the model performs when confronted with larger and more complex datasets, as well as its effectiveness in distinguishing between different types and stages of brain tumors. Moreover, the generalizability of the model to various healthcare settings and its potential integration with existing diagnostic procedures warrant further investigation. Future experiments might also delve into real-time applications and clinical trials to assess the model's impact on patient care.

In conclusion, my study demonstrates the promise of CNNs in automating brain tumor detection from MRI images, with the model achieving a mean accuracy of approximately 95%. While my results are significant in highlighting the potential for improved healthcare outcomes through automation, further research and validation are needed to fully integrate CNN-based diagnostic tools into clinical practice. The impact of this research lies in the potential to expedite brain tumor diagnoses, reduce delays in healthcare systems, and ultimately enhance patient care.

REFERENCES
DISTRIBUTION OF THE SPLIT OF 12,000 DATA IMAGES

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The data was split evenly between no tumor and each tumor type.

Figure 1. Comparison of tumor sample images. Image A is from a glioma tumor, image B is from a pituitary tumor, image C is from a meningioma tumor, and image D is from a healthy brain.

Figure 2. Architecture of my Machine Learning Model. The MRI is inputted, and the CNN decides whether it should be classified as glioma, meningioma, pituitary, or no tumor. This diagram is a visual illustration of this process.

Figure 3. The Relationship between Accuracy and Epoch Number. Line graph showing epoch number and accuracy had a direct relationship, meaning that as epoch number increased, accuracy also increased, with minor exceptions.
JAY PATEL was born in Hoboken, New Jersey, NJ, USA in 2007. He is currently a junior in the Academy for the Advancement of Science and Technology at the Bergen County Academies in Hackensack New Jersey.

Since 2023, he is a research intern at the BITS Lab at New York University. His research interests include machine learning, cancer biomarkers, and glioblastoma multiforme.

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