Brain Tumor Detection: Machine Learning Classification

University of Wisconsin - Madison

Computer Science 539 - Introduction to Neural Networks

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1 - Overview

The goal of this project is to create a convolutional neural network that will be trained for multi-class classification on several images of human brain MRIs. This image set will contain MRIs for individuals with three types of brain tumors — glioma, meningioma, and pituitary — in addition to a control sample of individuals with no tumor at all. The ultimate goal will be the classification of glioma, meningioma, pituitary, or no tumor.

2 - Background

Medical imaging analysis, while not a new field, is certainly a growing discipline with enormous potential for saving lives. With that being said, this abundant growth has not come without shadows of doubt around the technology — and for good reason. It is no surprise that patients would want another human to review MRI images, cell biopsies, or other scans to assure their cancer diagnosis, rather than relying on a pre-trained algorithm to confirm their diagnosis. In the United States today, cancer of all forms remains one of the leading causes of death across all cohorts [1]. And, while a doctor is still a necessary middle-man when diagnosing cancer with an algorithm, new research suggests that machine learning algorithms can diagnose diseases consistently with medical professionals [2]. Promising results with other diseases begs the question: why not apply deep learning methods to cancer image classification?

The current workflow when it comes to a brain tumor diagnosis typically begins with a series of neurological tests to assess brain function regarding balance, vision, and reflexes. Then, based on how these tests go, a doctor will order a scan of some sort (typically an MRI) and review the imaging results to determine if there is a tumor present in the brain. Then, finally, the doctor may order a biopsy of the suspected tumor to assess its type and whether or not it is cancerous [3].

It is easy to see where one may apply deep learning principles here. Instead of having doctors review these MRI images, healthcare professionals could instead look to deep learning algorithms to help assess these images. In fact, a recently published study found that deep learning models trained for brain tumor classification performed better in classifying and identifying brain tumors than neuroradiologists. Additionally, neuroradiologists that were provided with this same model outperformed their counterparts without the model in accuracy of diagnosing brain tumors [4].

3 - Statement of Work

3.1 - Datasets

This dataset is a compilation of three existing datasets from Kaggle and FigShare. Altogether, it contains 7022 MRI brain scans in a JPEG format. This directory contains 4 sub-directories, each of which corresponds to one of three types of brain cancer, with the fourth and final sub-directory containing images of brain scans with no brain tumor present. This collection of images is a composite of 3 separate data repositories found online, each one providing varying brain scans:

Dataset 1: Brain Tumor Dataset

Jun Cheng, Southern Medical University, Guangzhou, China

Cheng's provides a large portion of the entire sample. The imaging comes from brain scans of 233 different patients with different forms of brain tumors: meningioma (n=708), glioma (n=1426), and pituitary tumor (n=930).

Dataset 2: Brain Tumor Classification

@sartajbhuvaji on Kaggle

This dataset contains several more samples from each of the tumor types, as well a control set. The control samples (n=500) come from Navoneel Chakrabarty's Kaggle dataset (here). The remaining samples (meningioma (n=937), glioma (n=926), pituitary (n=901)) come from a private dataset published by Swati Kanchan, though these images are publicly available in the main dataset above.

Dataset 3: Brain Tumor Detection 2020

@ahmedhamada0 on Kaggle

This dataset contains data for binary classification of brain tumors. As such, we are only going to be using the "no tumor" subset (n=1500) in order to expand the size of our control group. We are opting not to use the images labeled as having a brain tumor as it would require a professional to manually label 1500 more images of brain tumors.

3.2 - Method

For our model, we plan on constructing and training a convolutional neural network (CNN) that is able to successfully classify the existence of tumors as well as their type from an MRI image. Currently, there is a large amount of work available online in the field of tumor classification, most of which takes a similar approach to that of our group. As mentioned in the background, this is a widely used method in the medical field due to its accuracy and cost-effectiveness. For example, the National Institute of Health released a study outlining the use of CNN's in tumor identification, specifically highlighting the contrasts between discriminate image analysis such as K-Nearest Neighbors (kNN), Artificial Neural Networks (ANN) and CNN's [5]. We want to explore tumor classification for our final project because it is a relevant application of this course's material and extends into the field of medicine. Further, this project will be utilizing tools that we will be learning in the coming weeks, so the development of this neural network will be an ongoing process and learning experience that naturally flows throughout the semester.

3.3 - Outcome and Performance Evaluation

For a baseline project, we will look at code from Kaggle user @jaykumar1607 (here), who created a CNN model based on dataset 1 above. This example has extremely good metrics for classification (avg. precision = 0.98, avg. recall = 0.98, avg. f1-score = 0.98). Further, the confusion matrix shows extremely low values for *Pr[Misclassification] = 2%.*

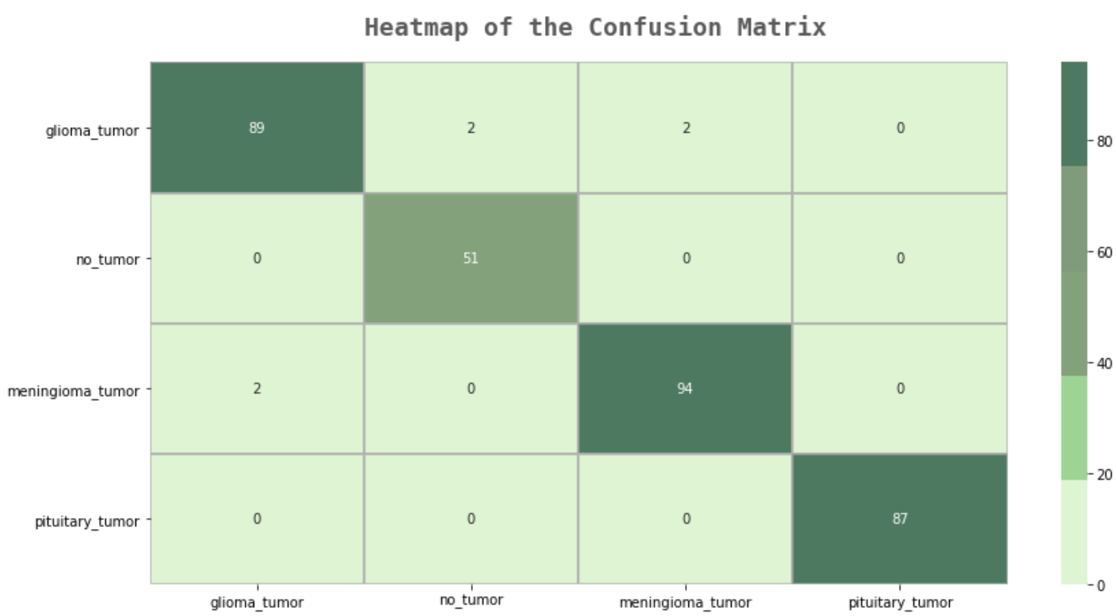

Figure 1: CNN Baseline Confusion Matrix

Based on course content and using this model as a guide, we hope that the addition of dataset 2 and dataset 3 will allow us to match and potentially surpass the performance of @jaykumar1607's model. Our initial goal is to begin with a CNN that is successful in binary classification of brain tumors. This will allow us to have a working model that successfully identifies where brain tumors are in these scans and what they look like. Following this successful binary classification model, we will expand the capabilities of our CNN to be a multiclass classification model capable of identifying the three different types of tumors present — namely meningioma, glioma, and pituitary tumors.

Because of the natural seriousness of brain tumors, we will be using f1 score as our primary testing statistic. In doing so, we effectively place an importance on minimizing the number of false negatives and false positives our model predicts. In this case, this means that we are minimizing the number of times we miss brain tumors and the number of times we incorrectly identify brain tumors — an approach we feel is the most realistic to take given the importance of a correct diagnosis in this situation. For our first model, we will define success as being an f1 score of 0.93 or higher. As for our second model, we define success as an f1 score of 0.95 or higher, with hopes that we will be able to match or surpass the f1 score of our baseline model.

4 - Project Plan

1. Initial Project Proposal
2. Initialize our environment (GitHub, Colab, etc.)
    - For this project, we will be writing the majority of our code in IPython-Notebooks (ipynb) hosted in Google Colab. Hosting our ipynb in Colab allows them to be collaborative, whereas an ipynb hosted on a virtual machine or on a local machine will not allow for collaborative development. Colab ipynb files will ultimately be uploaded to our GitHub repository, along with all of the other documents including the project proposal, figures and diagrams, and the final presentation slides.
3. Verify the baseline model
    - To validate the authenticity of our baseline model's f1 and accuracy scores, we will analyze the model's code and structure. From there, we will reevaluate the testing metrics across different train/test splits to assure its results are replicable.
4. Research optimizations
    - We will look through other existing models for brain tumor classification and medical image analysis to find potential optimizations that we can apply to our model.
5. Data preprocessing
6. Begin binary classification model
7. Submit project progress report

8. Train binary classification model — begin multiclass classification model
9. Test model
    - We will be testing our binary classification model on the testing portion of our train/test split. This requires us to feed the model untrained images from the same distribution and evaluate its accuracy afterwards. We will be logging the results of our tests as we re-evaluate to determine the best model.
10. Evaluate results
11. Visualize our results
12. Work on presentation
13. Work on final report

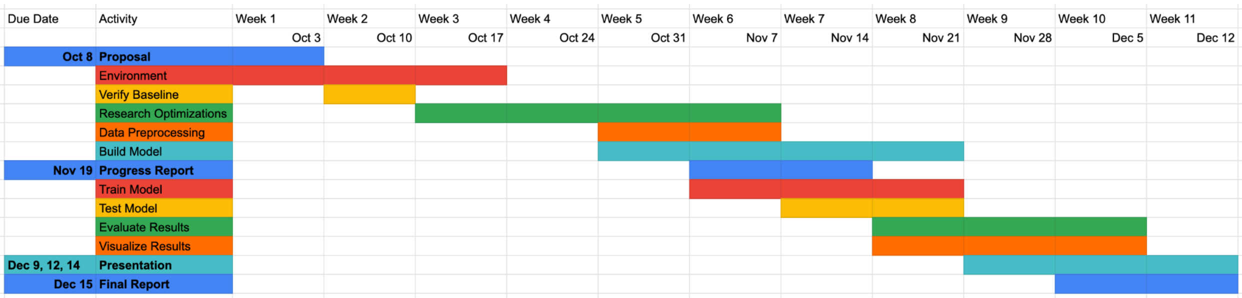

Figure 2 - Gantt Chart

5 - References

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[2] Gaël Varoquaux, Veronika Cheplygina. (2022, April 12). *Machine learning for medical imaging: methodological failures and recommendations for the future.* Springer Nature Limited. Retrieved October 1, 2022, from https://www.nature.com/articles/s41746-022-00592-y

[3] Johns Hopkins Medicine. *Brain Tumors and Brain Cancer*. The Johns Hopkins University. Retrieved October 1, 2022 from https://www.hopkinsmedicine.org/health/conditions-and-diseases/brain-tumor#:~:text=Diagnosing%20a%20brain%20tumor%20usually,%2C%20hearing%2C%20vision%20and%20reflexes.

[4] Gao P, Shan W, Guo Y, et al. *Development and Validation of a Deep Learning Model for Brain Tumor Diagnosis and Classification Using Magnetic Resonance Imaging*. JAMA Netw Open. 2022;5(8):e2225608. doi:10.1001/jamanetworkopen.2022.25608

[5] Díaz-Pernas, Francisco Javier et al. “A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network.” Healthcare (Basel, Switzerland) vol. 9,2 153. 2 Feb. 2021, doi:10.3390/healthcare9020153