**A-I 570 Scientific Reading & Research: Neural Network Tumor Diagnosis**

Accurate and timely tumor diagnosis is crucial to providing the best possible standard of care and treatment plan for a patient in need. This is especially true in the case of brain tumors, which are devastating and often aggressive, leaving those affected with 1-2 years of life remaining. The problem is, despite high level imaging techniques like MRIs, it can be quite difficult for doctors and specialists to fully interpret the results. For example, maybe they can definitively tell there is a tumor, but where does it start and where does it end? This is one of many interpretive challenges treatment teams face when interpreting results. A few other challenges faced by the doctors are determining the type, location, and grade of the tumor.

As a result, machine learning has begun to be applied to this problem, exploring whether or not algorithms can successfully identify tumors using image classification. While this is a cutting-edge practice, the potential is through the roof. Given high rates of accuracy, leaning on machine learning would enable the doctors to shift their focus immediately to a personalized treatment plan, rather than spending extra time in limbo trying unsure of the tumors dimensions. In order to enhance our understanding of the existing research and best practices, I found a few papers discussing tumor identification through neural networks. I will begin by discussing the first, “Challenges in Explaining Brain Tumor Detection”, then I will conclude with discussing “Advancing Early-Stage Brain Tumor Detection with Segmentation by Modified\_UNet”.

**Challenges in Explaining Brain Tumor Detection**

**Summary:**

AI and machine learning are becoming increasingly prevalent in healthcare and the medical industry. Right now, a lot of the usage is experimental, more testing related trying to determine functional applications and how to leverage the results. One of the challenges is understanding the conclusions reached by the algorithms and how to ‘trust’ these conclusions. Since the medical field has much higher stakes (life and death) than many other areas implementing AI and machine learning, it is crucial to understand the outcomes and not blindly trust the algorithms, even if they are correct. In order to tackle this problem, the authors sought to determine:

“R1 What is a good explanation for a brain tumor detection model?

R2 What brain tumor interpretable features should be detected by explanation techniques?

R3 How well do existing explanation techniques perform in the healthcare domain?”(Legastelois et al.)

In order to answer these questions, they used four different explainable AI models, with three of the four operating using different explanation methods in an effort to cover the whole landscape. Three of the four models (LIME, SHAP, and Integrated Gradients) used the entire dataset, while the fourth (DeepCover) used a subset as the training time is extreme. To evaluate and compare the performance, they define a few quantitative parameters for evaluation.

1. Size: how much of the image was covered by explanation?
2. Overlap: how much overlap was there between the different models’ explanations?
3. Comparison without DeepCover: since the other 3 models all used the full dataset, DeepCover was excluded for part of the comparison as it would not be a uniform comparison.
4. Execution time: how long does it take to go through the whole dataset?

Comparing the results, they found DeepCover to have performed the worst, which they suggest might be due to the algorithm itself. Additionally, they calculated DeepCover would take about 58 days to compete the whole dataset, while the next most intensive (LIME) took about 17 hours. LIME, SHAP, and Integrated Gradients had similar performance. In the end, the authors conclude that none of the techniques they employed proved robust explanations, highlighting the continuous challenges of relying on AI and machine learning in the medical setting.

**Aim & Challenges:**

The main focus and goal of this paper is to provide explanations for the results of CNNs used to identify brain tumors based on MRI imaging. Through comparing and analyzing different approaches, the authors seek to interpret and understand how the models reach their conclusion and reduce the “black box” element. The major challenge in explaining the results is the task itself. Due to the problem being deeply personal and traumatic, it is crucial to be able to explain the results in detail. This is different from other problems, because using the example from the paper, a model could classify animals based on their features and say this is a dog because of x, y, and z. With tumors, this becomes more complex because the classifications require more thorough and detailed explanations in order to be considered trustworthy. One example is defining the tumors borders. This is an extremely difficult task for the doctors as is, so if the models are able to successfully determine the borders, we must understand how they reached their conclusion. Another challenge discussed is there is currently no standard procedure for ‘grading’ explanations without the presence of the ground truth.

**Contributions:**

The main contribution of this paper in comparison to existing work is the effort to determine which technique provides robust explanations. Many other papers I saw, including the other paper I selected, focus largely on improving accuracy, while this paper attempts to provide insight into the black box of the classifications. Using four different explanation methods, LIME, SHAP, Integrated Gradients, and DeepCover, they were able to determine DeepCover is the least suited for this problem while the other three had similar results. While the results could have been more informative, they showcase the challenge of AI and machine learning in explaining medical images.

**Strengths & Weaknesses:**

I found the main strength of the paper to be the exploration of a challenging and problematic area with AI and machine learning in healthcare. There is a huge upside to using this technology in the healthcare field, but prior to large scale implementation, it is going to be integral to determine and apply techniques that will produce viable explanations. By looking into these challenges, the authors sought to advance the current knowledge and gain insight on beneficial methodologies.

A major weakness in their study is the lack of useful conclusions. They compared four methods, determining three of the four to have performed interchangeably. Additionally, they proved one of the methods, DeepCover is not an effective approach. While eliminating one of the options in the study is a good step, I would have liked to have seen a more comprehensive performance ranking.

**Project Relevance:**

Since our project is focused on brain tumors, I found it helpful to expand my understanding of the challenges associated with detection. I also feel that it will help me understand the results of our models, as the authors outlined great ways to compare the models based on results. Additionally, one of the datasets we are working with has no ground truth labels, so we can learn something from their analysis considering they did not have ground truth labels either.

**Advancing Early-Stage Brain Tumor Detection with Segmentation by Modified\_UNet**

**Summary:**

To begin, the authors outline the challenges and importance of brain tumor identification similar to my introduction above. They mention the rate of brain tumors per year has increased from 2021 to 2023, indicating this problem is more relevant than ever. Considering the limited amount of time post diagnosis, the goal of the paper is to improve the accuracy of existing early detection models allowing for an early and highly accurate diagnosis. The model used for the experiments is a transfer learning from Resnet to a modified U-net model, which conducts segmentation using a CNN. Two experiments were then conducted- one evaluating the Unet using three datasets of varying sample size, and one comparing the performance of the Unet to the performance of the modified Unet with the ResNet transfer learning. Their conclusions show the model using ResNet performed better than the initial Unet model.

**Aim & Challenges:**

The aim of the paper was to enhance the accuracy of existing early detection tumor models. Tumors detected early have displayed much better response to treatment, so through early diagnosis, the models would provide both more time for intervention and likely more productive results. The main challenge encountered appears to be the challenge encountered by all who take on this problem: determining the tumor’s boundaries. While the authors did not outwardly discuss struggling with issue, it was clearly a challenge based on the emphasis they placed on segmentation as a solution.

**Contributions:**

While most existing work has focused on tumor detection in general, this paper focused specifically on improving the accuracy of early-stage tumor predictions. Their ability to increase the accuracy and F-1 scores compared to a basic-Net is very meaningful, as early detection really boosts the likelihood of successful treatment. With a lot of things in the medical realm, time is everything, and in the case of brain tumors, this cannot be overstated. Improving the accuracy of early detection models pushes the existing research further and increases the amount of time the doctor has to save the patients life.

**Strengths & Weaknesses:**

In my opinion, the discussions of the model structure were a strength of this paper. First, the authors explained the architecture which is a modified UNet. Then they discuss using transfer learning from ResNet, with encoder and decoder blocks in order to conduct feature engineering and reconstruction which I found useful and potentially helpful for our project. The model then uses a CNN as the final classifier. After explaining the model, describe training the model over epochs and using a validation dataset to reduce overfitting. The thorough descriptions were very informative and helpful to understanding their model.

That being said, one weakness of the paper was the lack of details regarding the functions and algorithms used. The rest of the discussion on model creation was quite thorough, but these details were not included. Towards the end of the paper, the authors mention conducting an experiment to determine the best training and evaluation parameters. While they decided on F-1, IoU, Dice score, and accuracy score to evaluate the models, I was curious to read more about how they optimized the training. I was looking for comparisons of activation functions or optimization algorithms, but this topic was not expanded on. They did include epochs (50), batch size (32), and learning rate (0.001).

**Project Relevance:**

Considering our goals are to improve existing image-based classification models for brain tumor detection, this paper is very helpful and informative. Even though the paper focused specifically on early detection models, their discussions are insightful for refining the models we are creating. I think it would be a good idea to pursue the ResNet based transfer learning we mentioned previously; the encoder and decoder blocks mentioned in the paper seem to have been effective for feature engineering which is one area that can be challenging with images.

**References:**

Legastelois, Benedicte, et al. “Challenges in Explaining Brain Tumor Detection: Proceedings of the First International Symposium on Trustworthy Autonomous Systems.” *ACM Other Conferences*, 11 July 2023, dl.acm.org/doi/10.1145/3597512.3600208.

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