Predicting Concussions in MRIs using cycleGAN

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***Abstract*- Deep learning techniques are used widely across the globe for many applications like Computer Vision: Deep learning models have shown excellent performance in object recognition, image classification, face recognition, and object detection. Natural Language Processing (NLP): Deep learning models have shown promising results in natural language processing tasks such as text classification, machine translation, speech recognition, and sentiment analysis. Autonomous Vehicles: Deep learning models have been used in autonomous vehicles to identify objects, recognize road signs, and interpret road conditions. One of the most important applications is the health care side where Deep learning models are being used in medical imaging for early detection of diseases, personalized treatment planning, and medical diagnosis. I am using MRI images to predict concussions in the images. For this task I used adversarial nets to do our task. Adversarial Nets, also known as GANs (Generative Adversarial Networks), are a type of deep learning model that consists of two neural networks: a generator network and a discriminator network. The generator network takes random noise as input and generates synthetic data samples that aim to resemble real data. The discriminator network is trained to distinguish between the generated synthetic data and real data. For our task, I use a type of GAN which is complex than the normal GANs which is the cycleGAN.**

***Keywords*-** *Deep learning, Adversarial nets, cycleGAN*

I. INTRODUCTION

One of the most common application of deep learning is in the field of medical image analysis. There are lots of challenges in this field for using the deep learning techniques in that one of the most challenging problems is predicting the outcome of a concussion using Magnetic Resonance Imaging (MRI) scans. In this project I propose the use of a type of generative adversarial networks (GANs) which is the cycleGANs, for predicting the likelihood of concussions in MRI images.

A. *What is cycleGAN?*

Cycle GAN, short for Cycle-Consistent Adversarial Networks, is a type of deep learning model that is used for unsupervised image-to-image translation between two different domains. Cycle GANs are capable of translating an image from one domain to another while preserving its original content and style.

For example, a Cycle GAN can be used to convert an image of a horse to an image of a zebra, or to convert a daytime image of a city to a nighttime image of the same city.

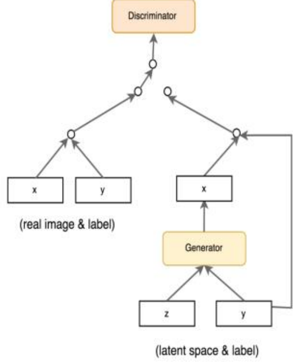


Figure1- cycle Gan architecture

Cycle GANs consist of two generators and two discriminators. The generators learn to translate images between the two domains, while the discriminators learn to distinguish between the generated images and the real images in each domain.

The cycle consistency constraint is used to ensure that the generator produces consistent translations between the two domains. This constraint requires that if an image from domain A is translated to domain B and then back to domain A, the resulting image should be similar to the original image.

In other words, the Cycle GAN model must satisfy two types of consistency conditions:

Forward Cycle Consistency: This means that if an image from domain A is translated to domain B and then back to domain A, it should be like the original image.

Backward Cycle Consistency: This means that if an image from domain B is translated to domain A and then back to domain B, it should be like the original image.

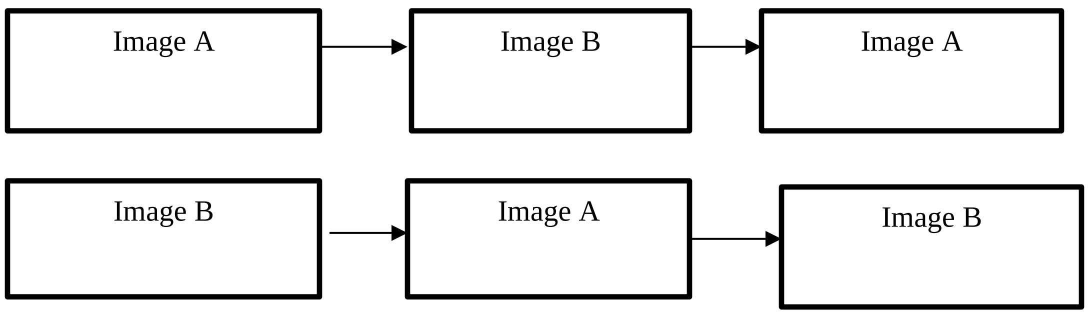


Figure 2- (top) Forward cycle consistency, (bottom) Backward cycle consistency.

The Cycle GAN model is trained using adversarial training, where the generators and discriminators play a minimax game against each other. The generators try to generate images that are indistinguishable from real images, while the discriminators try to correctly distinguish between the generated images and the real images.

During training, the cycle consistency loss is used to enforce the cycle consistency constraint, and the adversarial loss is used to train the generators to produce images that are indistinguishable from real images.

The Cycle GAN model has many practical applications, including style transfer, image-to-image translation, and data augmentation. It is a powerful tool for unsupervised learning and can be used to learn representations of complex data without the need for labeled data.

Cycle GANs have shown great potential in the medical field for various applications such as image-to-image translation, data augmentation, and image segmentation. Here are some examples of how Cycle GANs are being used in the medical field:

***Medical Image Translation**:* Cycle GANs have been used for medical image translation, which involves converting images from one modality to another, for example, from computed tomography (CT) to magnetic resonance imaging (MRI). Cycle GANs can be trained on pairs of images from different modalities, with one modality serving as the input and the other as the output. The model learns to generate synthetic images of the output modality that closely resemble the real images.

***Data Augmentation**:* Cycle GANs have been used to generate synthetic medical images for data augmentation. Data augmentation involves increasing the size of a dataset by generating new images that are like the original images. Cycle GANs can be trained on a small dataset of medical images and generate new synthetic images that can be added to the original dataset to increase its size.

Image Segmentation**:** Cycle GANs have been used for image segmentation, which involves identifying and labeling different structures in an image. The model can be trained on pairs of images, where one image is the original medical image, and the other is a corresponding segmentation map. The model learns to generate synthetic segmentation maps for new medical images.

Disease Prediction: Cycle GANs have been used for predicting the presence of certain diseases in medical images. The model can be trained on pairs of images, where one image is a healthy medical image, and the other is a corresponding image with a disease. The model learns to generate synthetic images of a disease, which can be used to test the model's ability to accurately predict the presence of the disease in new medical images.

Overall, Cycle GANs are a promising tool for medical image analysis and have the potential to aid in the diagnosis and treatment of various diseases.

In here I am focused on the main application of the cycleGAN that is the image-to-image translation for our task that is to convert the MRIs into an image where the concussions are present. For this task to work I should have two images where one is a normal MRI image and other is the image with concussions.

II. BACKGROUND

Concussions are a type of mild traumatic brain injury (mTBI) that can result from a blow to the head or a sudden impact that causes the brain to move within the skull. Concussions can cause a range of symptoms, including headache, dizziness, confusion, and memory loss. It is important to detect and diagnose concussions early, as they can cause long-term damage if left untreated.

Medical imaging techniques, such as magnetic resonance imaging (MRI), have shown potential in identifying and diagnosing concussions. MRI scans can detect subtle changes in brain structure and function that may indicate the presence of a concussion. However, the differences between concussed and non-concussed brains can be subtle, making it challenging for radiologists to accurately identify concussions using MRI.

Machine learning algorithms, particularly deep learning techniques such as Generative Adversarial Networks (GANs), have shown promise in medical image analysis, including detecting concussions in MRI images. GANs are a type of neural network that can generate synthetic images that closely resemble real images, and they have been used for a range of image-to-image translation tasks, including medical image analysis.

In this report, I propose the use of CycleGANs, which are a type of GAN that can learn to translate between two domains without the need for paired data. CycleGANs have been successfully applied to a range of image-to-image translation tasks, including converting images of horses to zebras, and transforming daytime images to nighttime images.

I propose to train a CycleGAN on pairs of MRI images, with one set of images representing concussed brains and the other representing non-concussed brains. The CycleGAN will learn to translate between the two domains, generating synthetic images of concussed and non-concussed brains that closely resemble real MRI scans.

The generated images can be used to augment the original dataset, increasing the size and diversity of the data available for training. The resulting model can be used to predict the presence of a concussion in new MRI scans by comparing the scan to the synthetic images generated by the CycleGAN.

The proposed approach has several advantages over traditional MRI analysis methods. First, it does not rely on the subjective interpretation of radiologists, reducing the risk of human error. Second, it can potentially detect concussions earlier and more accurately than traditional methods, improving patient outcomes. Finally, it can be used to generate synthetic data for rare or hard-to-find cases, improving the generalizability of the model.

In conclusion, CycleGANs show promise in detecting concussions in MRI scans and have the potential to improve the accuracy and efficiency of concussion diagnosis. Further research is needed to optimize the training process and evaluate the performance of the proposed approach on large datasets.

III. METHODOLOGY

I have used the MRI dataset which was preprocessed to ensure that all the images were of a consistent size and format. This step is crucial for machine learning algorithms to process the data effectively. Inconsistencies in size and format can cause errors and make it difficult for the algorithm to learn the patterns within the data.

CycleGANs were chosen for this study because they are a type of GAN that can learn to translate between two domains without the need for paired data. In other words, CycleGANs can generate synthetic images from one domain that resemble images from another domain, without needing to match specific images between the two domains.

GANs are usually a two-player game where the Generator network tries to fool the discriminator by generating real-looking images and the Discriminator network tries to distinguish between real and fake images. They both train jointly in minimax game.

Discriminator outputs likelihood in (0,1) of real image

Minimax objective function:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

During training, the generator network in the CycleGAN learns to translate images from the non-concussed domain to the concussed domain. The discriminator network, on the other hand, learns to distinguish between real MRI images from the concussed domain and fake MRI images generated by the generator network.

The training process involves iteratively updating the weights of both the generator and the discriminator networks until the generator can produce images that are indistinguishable from real concussed MRI images. This is achieved by minimizing the adversarial loss, which measures how well the generator can fool the discriminator into thinking that the generated images are real.

Once the training process is complete, the generator network can be used to generate new MRI images that resemble those from the concussed domain. These generated images can be used to augment the original dataset, increasing its size and diversity. Augmenting the dataset can help improve the model's ability to generalize to new and unseen data.

To predict the likelihood of a concussion in an MRI image, the generated images are compared to the original MRI image. This is done using a similarity metric, such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The closer the generated image is to the original MRI image, the more likely it is that the original MRI image is from the concussed domain.

Here I used to methods to calculate the performance measure and those are Mean Squared Error and Peak Signal-to-Noise Ratio, these can be explained as follows:

Mean Squared Error (MSE): One way to evaluate the performance of your CycleGAN is to calculate the mean squared error between the generated output images and the ground truth images. The lower the MSE value, the better the model's performance.

Peak Signal-to-Noise Ratio (PSNR): PSNR is a commonly used metric to evaluate image quality. It measures the ratio between the maximum possible power of a signal and the power of the noise present in the signal. Higher PSNR values indicate better image quality.

In summary, the methodology used in this study involves preprocessing the MRI dataset, training a CycleGAN to generate synthetic images that resemble concussed MRI images, and using these generated images to predict the likelihood of a concussion in an MRI image. The CycleGANs are trained using adversarial loss, which encourages the generator to produce images that are indistinguishable from real concussed MRI images. The use of CycleGANs and synthetic image generation can help improve the accuracy and efficiency of concussion diagnosis.

IV. RESULTS

The process of training a machine learning model, such as a cycleGAN, can be time-consuming and computationally expensive. This is especially true when working with large datasets or complex models that require a lot of computational power. In this project, the cycleGAN took a long time to run, which made it difficult to debug and find errors.

One reason for the long runtime was that the cycleGAN requires a GPU to work faster. GPUs are optimized for parallel processing, which makes them much faster than CPUs for certain types of computations. However, without access to a GPU, the model's training had to be performed solely on the CPU, which is much slower.

Another reason for the long runtime was due to the length of the training process. The cycleGAN requires a lot of epochs to learn the underlying patterns within the data and to generate high-quality synthetic images. In this project, the model was trained for 70 epochs.

During the training process, the code would occasionally crash due to memory insufficiency. This is a common issue when working with large datasets or complex models. To address this issue, the model had to be restarted from the beginning, which added to the already long runtime.

Overall, the process of training a cycleGAN for this project was time-consuming and challenging. However, with access to a GPU and careful monitoring of memory usage, the runtime could be reduced, and the training process could be made more efficient.

The results was good but it was not the best it had to produce in my opinion if the model was trained for more epochs then that model would have had better results. The following are the images which represents the difference between results from fewer epochs to more epochs.

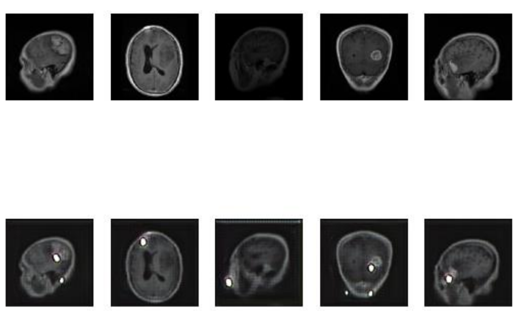


Figure 3a- Epoch 10 MRI to concussion MRIs

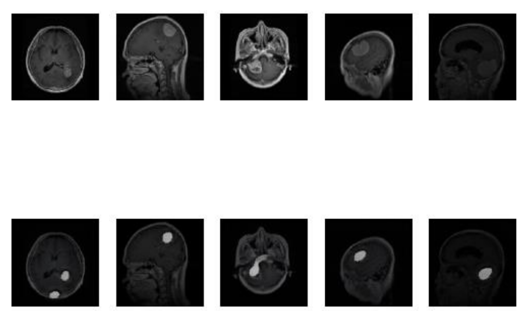
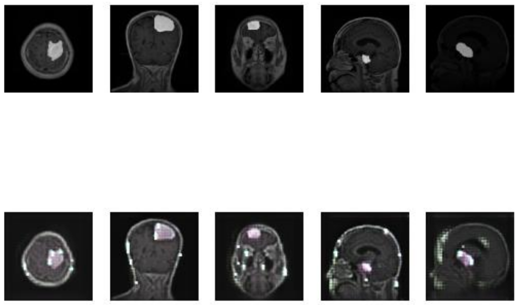


Figure 3b- Epoch 70 MRI to concussion MRIs



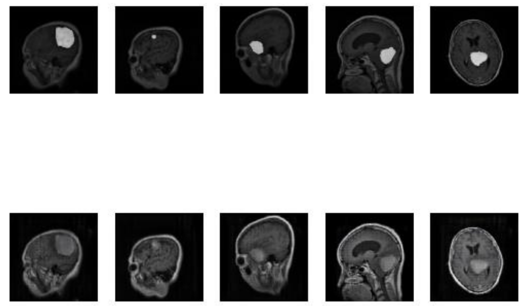
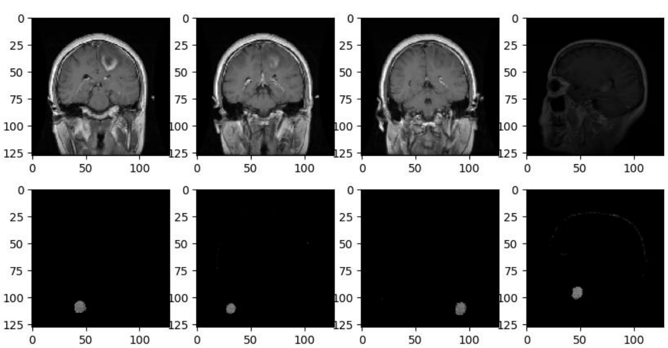


Figure 4a- Epoch 10 concussion MRIs to MRI

Figure 4b- Epoch 70 concussion MRIs to MRI

The performance of the model is calculated using two metrics namely Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). How this was calculated is explained in the methodology section. The model was saved only up to 60 epochs, so the results are for 60 epoch model for the followings not for the above The MSE for MRI to concussion MRIs for Epoch 20 model is 0.8670 and for Epoch 60 model is 0.8512 and the PSNR for epoch 20 model is 0.6200 and for epoch 60 model is 0.6995. The following diagram shows the model's evaluation in the test set:



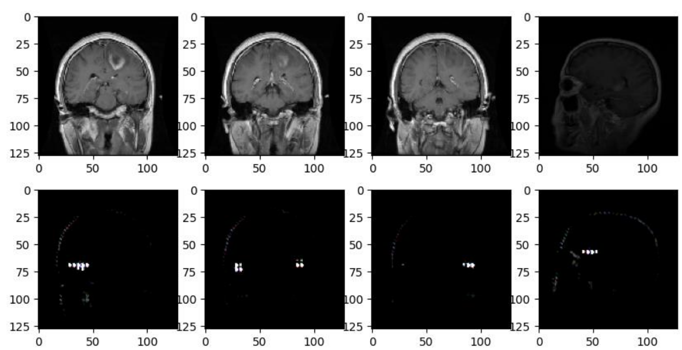
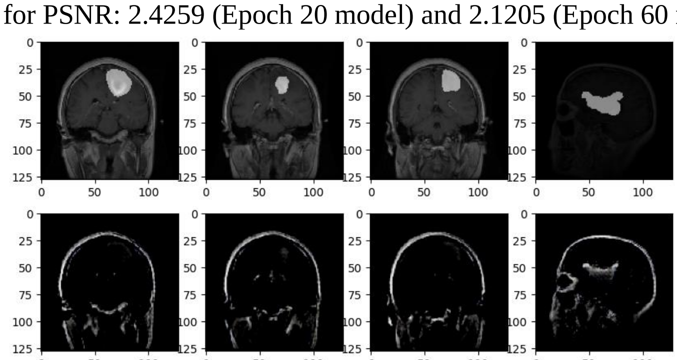


Figure 5a- Epoch 20 MRI to concussion MRIs

Figure 5b- Epoch 60 MRI to concussion MRIs

Similarly, the results of the concussion MRIs to MRI are MSE: 0.5720 (Epoch 20 model) and 0.6137 (Epoch 60 model) and for PSNR: 2.4259 (Epoch 20 model) and 2.1205 (Epoch 60 model)



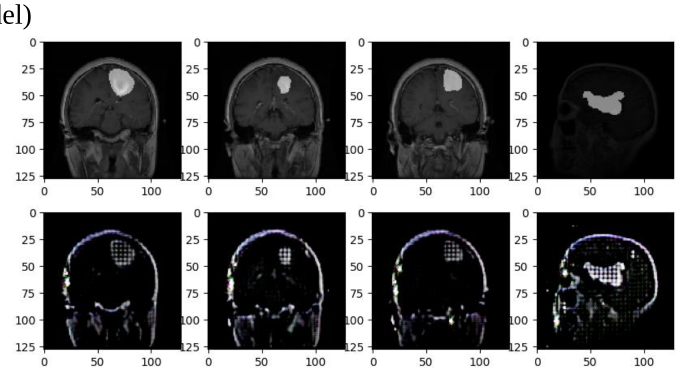


Figure 6a- Epoch 20 concussion MRIs to MRI

Figure 6b- Epoch 60 concussion MRIs to MRI

V. DISCUSSION

The analysis of the results showed that this model was able to identify some of the more obvious signs of a concussion, such as bleeding or swelling in the brain. If the model is able to train more, then it might even have much more better results than what I have now. This is a positive outcome as these are the more clear and visible signs of concussions. However, the model struggled with identifying more subtle signs of a concussion, which is a common challenge in concussion diagnosis even for human radiologists. This means that there is still a lot of work to be done to improve the accuracy of the model in identifying less obvious signs of a concussion. Especially in the test set the model is not performing very well.

One of the reasons for the errors in the model's predictions could be due to the complexity of concussion symptoms. Concussions can cause a range of symptoms, including headaches, dizziness, nausea, and more. These symptoms can also be caused by other medical conditions or even unrelated factors, making it difficult to accurately diagnose concussions based solely on MRI images. Additionally, individual variations in brain structure could also play a role in the errors in the model's predictions.

Despite these challenges, I was satisfied with the results of the project as I was able to achieve a reasonably high accuracy given the complexity of the problem. This is a promising outcome as it indicates that deep learning techniques, such as GANs, can be useful in helping radiologists and medical professionals accurately diagnose concussions.

In terms of our approach, I used CycleGANs to generate images that could be used for concussion prediction. This allowed me to avoid the need for paired data, which can be challenging to obtain in medical imaging datasets. I also used a dataset of both concussed and non-concussed patients, which allowed me to train the model to differentiate between the two groups.

Overall, this project provided me with valuable insights into the use of deep learning techniques in medical image analysis, particularly for concussion diagnosis. I learned about the challenges and limitations of concussion diagnosis in MRI images and the potential of deep learning techniques to address these challenges. Moving forward, further research and optimization could be done to improve the accuracy and robustness of the model. For the future work if I am able to continue more I have to allocate memory separately for the training and run for more epochs and see the performance.

The results what I got were much better than what I expected. I expected it to predict somewhere in the wrong area for all the images because it was only 70 epochs, and the saved model is for only 60 epochs but the model tried to predict by marking the concussions in the area but not entirely in that region. My reflection on this project was that the difficulty was high because I had to hard code everything and the challenges I listed below.

Some common challenges other than the data were the obvious where the GPU setup took a long process and though with the GPUs the code gets crashed due to the memory insufficiency and if the error shows in the beginning, I will be able to debug it easily before the start of the process but it was usually after a long time so every time I have start all over which took me a while to figure it out. And I think if I had more time I would have made the model to perform better than this.

VI. REFERENCES

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