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Integrating Stable diffusion for Improved Alzheimer's Disease Classification: Insights from MRI Images and YOLOv8

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***Abstract*—Alzheimer's disease (AD) is the most common form of dementia, characterized by progressive neurodegeneration. Structural changes in the brain associated with AD can be visualized using magnetic resonance imaging (MRI). However, acquiring a sufficient number of MRI images from patients with Alzheimer's disease is challenging. In this study, we employ stable diffusion to simulate MRI scans of patients with AD. We train the stable diffusion model from scratch to generate new MRI images as part of data augmentation alongside the original images. The model is capable of producing synthetic MRI images of AD. We employ t-distributed Stochastic Neighbor Embedding (t-SNE) visualization to evaluate the quality and diversity of the generated images by comparing their distribution to that of actual MRI scans. Subsequently, a modified YOLOv8-cls model is retrained using the generated images for AD classification. Our findings demonstrate that this approach effectively produces realistic synthetic biological images suitable for training deep learning models with 10% improvement in accuracy.**

Keywords*: *Generative model, stable diffusion, Alzheimer's disease, MRI image, deep learning

I. Introduction

With over 50 million cases globally, Alzheimer's disease (AD) is the most frequent cause of dementia. It is anticipated that the prevalence of AD will sharply increase as the population ages. Currently, a post-mortem brain examination is necessary for a conclusive diagnosis of AD. However, magnetic resonance imaging (MRI) has become a viable method for observing anatomical alterations in the brain linked to the advancement of AD. When applied to structural MRI data, machine learning techniques have demonstrated growing value in supporting the timely and precise diagnosis of AD [2]. High performance for AD classification from MRI data has been attained by deep learning models such as Yolo models [1]. However, large labeled training datasets are necessary for these models, but obtaining them for medical imaging applications is costly and time-consuming. Recently, it has been shown that generative models, such as GANs, have successfully created new images. However, basic GAN models [3] offer less control over the specific details and styles of generated images. In contrast, stable diffusion (SD) models allow for more fine-grained control over the quality of generated images, enabling users to specify desired properties or characteristics in the generated data more effectively.

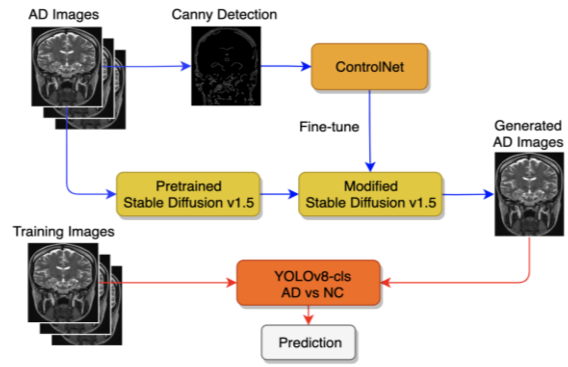

Figure 1. Overflow of stable diffusion training (blue) and classification model (red).

In this study, we trained a stable diffusion (SD) model from scratch using existing MRI images of AD patients. Stable diffusion generates varied and high-quality images with less data, making it efficient for producing synthetic data of high quality [5]. We then utilized the resultant images to enhance the training of a YOLOv8-cls model for AD classification, where YOLOv8-cls is from Ultralytics[1] frameworks. Our experiments highlight the utilization of stable diffusion for data augmentation and the enhance of YOLOv8 in identifying AD biomarkers within MRI data.

II. Proposed Method

Our proposed idea is evaluated on MRI images collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database[2]. We use 500 coronal view images extracted from 100 patients split 80% and 20% across training and validation respectively, following the settings of [4]. The dataset will be split into 2 classes: Alzheimer disease (AD) and Normal control (NC). The original images are preprocessed, by downsizing the image size to 128x128 pixels. Using the stable diffusion model, the 400 original AD images are fed into the model with the LORA architecture to train the stable diffusion (SD) model. To fine-tune specific details, we employed ControlNet to guide the generated images. ControlNet provides more precise structural control of the MRI images, including edge detection. With the Canny edge detection, we aim to control the skull shape of the brain in the coronal view. As shown in Figure 1, our combined model operates in parallel to produce high-quality AD images.

Training details: The stable diffusion v1.5 from the kohya_ss framework [3] was configured with the following parameters: sampling method: DPM++2M karras, sampling steps: 20, width: 512, height: 512, batch count: 100, batch size: 10, CFG scale: 7, seed: -1. Image production control was

[1] https://github.com/ultralytics/ultralytics
[2] https://adni.loni.usc.edu/
[3] https://github.com/bmaltais/kohya_ss

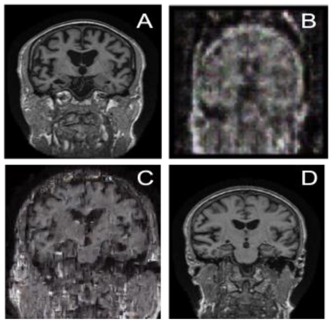

Figure 2. Comparison between the original AD image (A) and AD generated images using DC-GAN (B), Stable Diffusion without ControlNet (C) and with ControlNet (D).

facilitated by the ControlNet module v1.1.423 in stable diffusion. A total of one hundred newly generated AD MRI scans were produced. Figure 1 illustrates the generated image from stable diffusion. The combination (AD+AD generated images) is used to train a baseline YOLOv8-cls, keeping the settings and training parameters such as optimizer, image size, and augmentation consistent.

III. Result and Discussion

Figure 2 illustrates the comparison images. Image A depicts the original AD image, while image B shows the image generated using DC-GAN, and image C and D represent generated images with SD. In B and C, the images display unclear brain shapes and lack certain organ details when using DC-GAN and stable diffusion without ControlNet. However, as shown in D, after fine-tuning with ControlNet, which employs Canny detection to identify skull boundaries, the resulting brain images appear more natural. These finely-tuned images, like D, are utilized for training YOLOv8-cls. Prior to training, t-SNE is performed to identify clusters or patterns and compare the distribution of the newly generated AD images with that of actual AD MRI images. As depicted in Figure 3, the t-SNE visualization demonstrates the synthetic and original AD MRI scans, indicating that SD captures features relatively close to the original AD images.

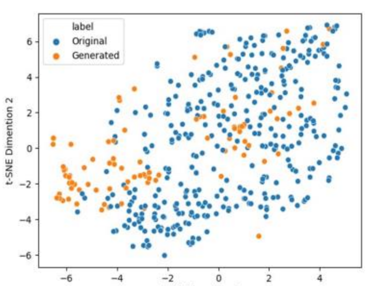

Figure 3. t-SNE Visualization of our AD generated image and original AD images.

Our observation on AD classification using YOLOv8, trained solely on the original 400 AD MRI images, yielded an accuracy of 0.79. However, upon incorporating an additional 100 generated AD MRI images into the training set represent 20% of the orginal images, the accuracy increased to 0.889. In Figure 4, we observe that the increase in True Positives (TP) for the AD class from 0.75 to 0.85 can be attributed to the enhanced discriminative capabilities of the model resulting from the inclusion of newly generated samples from stable diffusion.

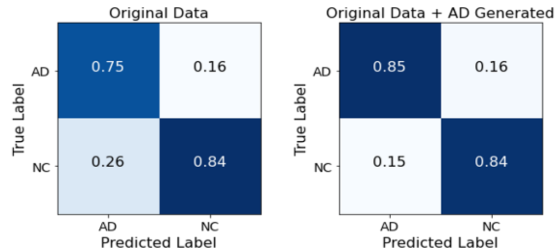

Figure 4. Comparison of AD vs NC classification results with YOLOv8-cls. The confusion matrix without additional stable diffusion (left) and with the inclusion of stable diffusion-generated images (right).

These synthetic samples likely offer a more diverse representation of AD images, capturing a broader spectrum of features and patterns characteristic of Alzheimer's disease. Consequently, the model becomes more adept at recognizing and classifying instances of AD accurately. Moreover, augmenting the training data with synthetic samples may have helped address issues related to class imbalance or data sparsity, thereby facilitating more robust learning and improved performance, particularly in identifying AD cases.

IV. Conclusion

This study explores utilizing generative AI to enhance deep learning for Alzheimer's detection through synthetic MRI augmentation from stable diffusion. The results show that incorporating realistic images generated by stable diffusion improves MRI classification accuracy. Future works will focus on enhancing the process by automatically generating and utilizing images for all planes of 3D MRI scans

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