Enhanced Brain Tumor Detection using U-Net and GAN-based Colorization

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***Abstract*—Medical imaging has made progress in detecting and diagnosing brain tumors at a stage. In our research paper we present a method that combines the capabilities of UNet, a neural network architecture with Generative Adversarial Networks (GANs) to improve brain tumor detection through image colorization. This project leverages a deep learning-based colorization model to enhance brain tumor visualization in MRI images. By training on diverse data sources, we employ a U-Net model with GAN-inspired components. The model enhances grayscale MRI scans by adding color, aiming to aid in tumor detection. Our method utilizes the UNet structure to analyze grayscale images and accurately identify areas that contain tumors. We then employ colorization techniques based on GANs to add color to these segmented regions making them visually distinct and easily distinguishable. By combining these two neural network architectures our approach not only helps locate tumors but also improves their visibility and differentiation, from healthy brain tissue.**

***Index Terms*—Medical imaging, Brain Tumor, U-Net, Generative Adversarial Networks (GANs), Image Colorization**

I. Introduction

A. Background Information

Early and precise identification of brain tumors is crucial, for treatment and patient results. Within the field of imaging there have been advancements in utilizing deep learning techniques to detect brain tumors. In this context we introduce a method that combines the strengths of U Net, a convolutional neural network (CNN) architecture well known for its ability to perform semantic segmentation with Generative Adversarial Networks (GANs) which are renowned for their expertise in image colorization.

Brain tumors are a major challenge in radiology, requiring improved equipment for early detection. It has the potential to be a game-changer in this area, offering a new perspective on medical imaging and diagnosis. In this paper, we explore the complexities of our methodology, discuss its structure, mechanism, and promising radiological implications. Through extensive testing and evaluation, we demonstrate the tangible benefits of our approach, paving the way for more accurate and timely brain tumor diagnosis, ultimately improving patient care.

B. Overview

This paper introduces a new technique designed to improve the detection of brain tumors in medical images. The main innovation is to combine U-Net for accurate tumor classification with GAN-based image colorizing for enhancing visual cues, making tumor areas more visible and distinguishable Through these two neural networks, we aim not only to localize tumors but also to provide physicians with advanced visual imaging to facilitate rapid and accurate diagnosis.

II. Literature Survey

There are areas of computer vision research that are connected and combined in the colorization process. Colorization research papers can be quite diverse because of the methods proposed to solve the problem. It is quite challenging to characterize the colorization methods due to their varied approaches.

The paper [1] presents a new technique for gray scale image colorization based on Convolutional Neural Networks (CNNs) where Inception ResNet V2 is used as feature extractor. However to get a proper colored image it needed to run alot of epochs and often the results were of low quality and full of artifacts.

The paper [2] presents a deep learning-based technique for colorizing grayscale images. The authors employ a combination of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to achieve realistic colorization results. Its problem was it did not pick colors accurately in many scenarios, so it covered those regions with reddish/brown.

The paper [3] proposes a technique for colorizing gray scale images of human faces using deep learning-based methods.

Their method includes a way to train the autoencoder model where encoder and decoder networks are present. They treated the image colorization problem as a regression problem.The limitation was that autoencoders rely heavily on colors present in the training data resulting in colorizations that closely resemble the average colors in the dataset. Moreover it was specific for human faces and failed to perform in other scenarios.

The paper [4] proposes a prototype for integrating colorization and super resolution models using machine learning techniques. The idea was that the combined model will take in old, blurry, hazed images as input and produce colorized, detailed and high-resolution images as an output. Its limitation was that it could only predict a limited class of colors and it focused more on resolution than clarity.

III. Dataset Description

A. Source

For model training: The COCO dataset was created and is maintained by Microsoft Research. It has been made publicly available to support research in image analysis, object recognition, and related fields.

MRI Images: The dataset is available on Kaggle, a popular platform for hosting and sharing datasets for various machine learning and data science tasks. It can be accessed through the Kaggle dataset repository, and users can download the dataset to use it for research, development, and educational purposes.

B. Description

The COCO dataset is a widely-used collection of images consisting of a large collection of images with diverse object categories and detailed annotations. It is commonly used for computer vision tasks such as image segmentation, object detection, and image captioning. The dataset includes over 200,000 images with 80 different object categories, making it valuable for training and evaluating machine learning models in the field of computer vision.

The Brain Tumor MRI Images dataset is a collection of medical images that includes MRI scans of the brain with different types of tumors. This dataset is specifically designed for the task of classifying brain tumors into four categories: glioma, meningioma, no tumor, and pituitary. These images are essential for developing machine learning models aimed at automating the diagnosis of brain tumors based on MRI scans.

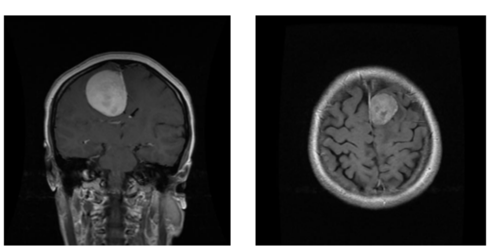

Fig. 1. MRI Images - showing presence of tumors

IV. Methodology

In this section, we provide an overview of the methods used to improve the visibility and identification of brain tumors in MRI images using a deep learning-based colorization model. The study uses a multi-stage methodology that begins with model training on a variety of datasets and ends with the application of the learned model to medical MRI scans.

A. Data Collection and Preprocessing

1) Training Data: A vast collection of different photos is used to train a colorization model at the core of our strategy. We used the Common Objects in Context (COCO) dataset, which includes a variety of real-world photos, for this project. Despite not being of a medical nature, the COCO dataset is an important source of information for the model's training to comprehend color correlations.

2) Preprocessing: Prior to training, the training dataset underwent preprocessing, which included the following steps:

- Resizing: All images were resized to a consistent resolution suitable for the model.
- Color Conversion: Images were converted from the RGB color space to the Lab color space. This conversion is pivotal for the colorization task as it separates the grayscale "L" channel from the "a" and "b" channels, representing color information.

B. Model Architecture & Training

Generator Model: To implement our generator model, we used a U-Net architecture. The U-Net has a reputation for being efficient at translating images into other images. U-Net is a convolutional neural network architecture used for tasks like image segmentation and image-to-image translation. For the purpose of maintaining spatial information during upsampling, the model comprises of an encoder-decoder structure with skip links. The encoder part captures contextual information by gradually downsampling the input image. The decoder part then performs upsampling while using skip connections to recover finer details from the encoder.

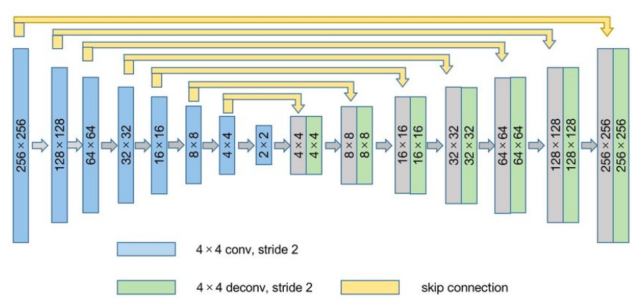

Fig. 2. U-Net Architecture

Discriminator Model: A patch discriminator was used to assess the realism of the colorized images. This discriminator produces multiple real/fake judgments for patches of the image, allowing for more precise feedback during training.

Instead of providing a single scalar output like a traditional discriminator, a Patch Discriminator produces multiple outputs for different patches of an image. Each output represents whether a particular patch of the image is real or fake. Patch Discriminators are especially useful for tasks where local details in an image matter, such as image-to-image translation or image generation.

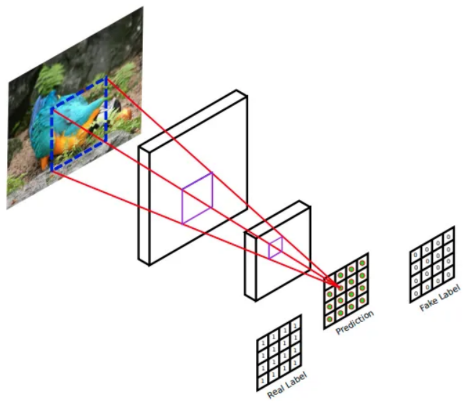

Fig. 3. PatchGAN discriminator. The output is a matrix and each element in the matrix represents a local region in the input image. If the local region is real, we should get 1, else 0.

Loss Functions:

- Adversarial Loss (GAN Loss): To promote the generation of realistic-looking colorized images, we introduced an adversarial loss based on the principles of Generative Adversarial Networks (GANs).

$$\begin{aligned}\mathcal{L}_{cGAN}(G,D) =& \mathbb{E}_{x,y}[\log D(x,y)]+ \\ & \mathbb{E}_{x,z}[\log(1-D(x,G(x,z))]\end{aligned}$$

Fig. 4. Conditional GAN Loss function

- L1 Loss: To ensure colorization accuracy, we incorporated an L1 loss (mean absolute error) that measures the difference between the predicted and ground truth color values.

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1]$$

Fig. 5. L1 Loss function

Training Strategy: The training process involved a two-step approach:

- Pretraining: In this stage, the generator model was pretrained in a supervised manner using only L1 loss. This helped establish a foundation for colorization before introducing adversarial training.
- Adversarial Training: Following pretraining, the model was further trained using the combined adversarial and L1 loss. This adversarial training aimed to refine colorization results and enhance image realism.

$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda\mathcal{L}_{L1}(G)$$

Fig. 6. Combined Loss function

where lambda is a coefficient to balance the contribution of the two losses to the final loss (of course the discriminator loss does not involve the L1 loss).

C. Applications to MRI Images

Data Acquisition: For the application of the colorization model to medical MRI images, a dataset of grayscale MRI scans was collected. These scans served as the input for the colorization process.

Colorization: The pretrained and fine-tuned colorization model was applied to the MRI scans. The model takes the grayscale MRI images as input and generates colorized versions by predicting the ”a” and ”b” channels in the Lab color space while preserving the ”L” channel.

D. Visualization & Brain Tumor Detection

Colorization Visualization: The primary objective of colorization was to enhance the visual interpretation of MRI scans. Colorized MRI images were examined to determine how effectively the model added color to the grayscale scans, thereby improving the visualization of anatomical structures and abnormalities.

Brain Tumor Detection: The colorized MRI images were also used for brain tumor detection. Medical professionals and image analysis algorithms were employed to detect and analyze any abnormalities or potential brain tumors in the color-enhanced images. The colorization process aimed to provide additional visual cues that might aid in the detection process.

V. Results

The results obtained were visually impressive. The colorized MRI images allowed for a more detailed and informative representation of the brain scans, enhancing the visibility of anomalies such as tumors. This colorization process significantly improved the interpretability of the MRI scans, making it easier for medical professionals to identify and assess brain abnormalities.

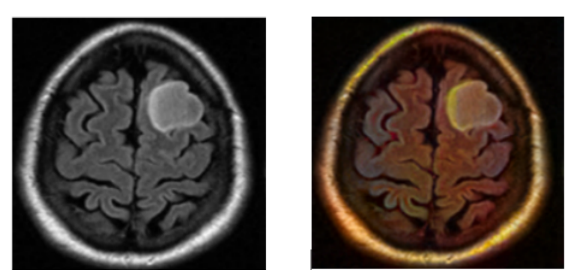

Fig. 7. Original image vs. colorized image - Glioma Tumor

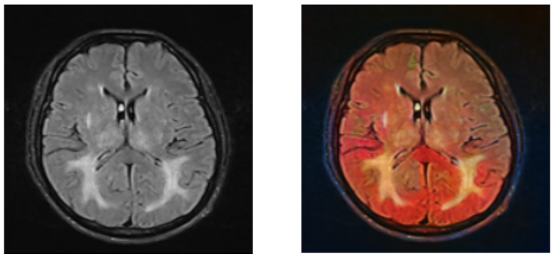

Fig. 8. Original image vs. colorized image - No Tumor

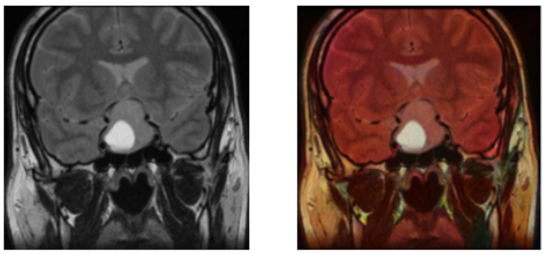

Fig. 9. Original image vs. colorized image - Pituitary Tumor

VI. Conclusion

In conclusion, this project demonstrated the potential of deep learning and colorization techniques to enhance the analysis of medical images, specifically in the context of brain tumor detection using MRI scans. The application of colorization to medical imaging has promising implications for the field of radiology and healthcare. It can potentially aid medical professionals in the early detection and diagnosis of brain tumors, ultimately leading to improved patient outcomes. Moreover, the methodology presented here can be extended to other medical image analysis tasks, opening up new avenues for research and innovation in the medical field.

While the results are promising, it's essential to acknowledge that this project represents just one step toward improving medical image analysis. Future work may involve refining the model further, optimizing it for specific medical imaging tasks, and conducting rigorous clinical evaluations to assess its real-world utility. Nevertheless, the colorization of MRI images shows great potential as a tool for improving the interpretation and diagnosis of brain tumors and other medical conditions.

VII. Acknowledgment

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