Detecting AI-Generated Images using ResNet

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Abstract

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1 Introduction

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2 Related Work

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3 Datasets

In order to train a classifier that can distinguish between real and generated images, we need a labeled dataset that consists of both real and generated images for supervised learning. Datasets of this kind is not common, and we'd like to experiment on the latest state-of-the-art image generation AI models, such as DALL·E 2 and Stable Diffusion. We started with real photos from existing public datasets as our raw datasets. Then, we use Diffusers-based image-to-image model to generate image variations from real photos. This way, we can get a labeled dataset that consists of both real and generated images.

3.1 Raw Datasets

The original real-world photos we experimented with are from public datasets: Indoor Scene Recognition Database and Weather Image Recognition Dataset. Additionally, we want to test how well our model performs on non-photo art work. A dataset that consists of pages of comic art (the Comic Books Images Dataset) is also used in our experiments.

3.1.1 Indoor Scene Recognition Dataset

Originally targeting at indoor scene recognition tasks, the Indoor Scene Recognition Database is a collection of 67 indoor categories (e.g. airport, living room, restaurant...) and at least 100 images per category (**?**). There are 15,620 images in the dataset in total. Figure **??** shows some examples of the dataset.

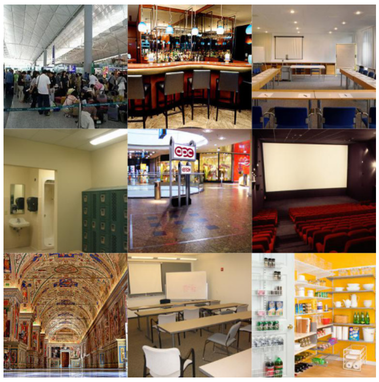

Figure 1: Indoor Scene Recognition Database Examples

This dataset is the biggest among the three datasets we used and serves as our main dataset. We use the AI-generated variations from these images and the images themselves to train our classifier.

3.1.2 Weather Image Recognition Dataset

The Weather Image Recognition Dataset contains labeled 6738 images of different types of weather, its catogories including dew, fog, frost, glaze, etc (**?**). This dataset is used in our experiment to evaluate our model's generalization ability and performance on other kinds of photos than indoors.

./assets/paper_weather_dataset.jpg

Figure 2: Weather Image Recognition Dataset Examples

3.1.3 Comic Books Images Dataset

The Comic Books Images Dataset is an open source dataset from Kaggle that contains 512 images from comic book pages (**?**). Although our goal is to build a classifier to detect AI-generated photos versus real photos, and comic art seems to fall in neither category, we want to test whether our model can detect AI-generated comic art verses real comic art. This can further verify the generalization of our model. We what use to evaluation is a subset of this dataset, containing 513 images. Figure **??** shows some examples of the dataset.

./assets/paper_comic_dataset.jpg

Figure 3: Comic Books Images Dataset Examples

3.2 Image-to-Image Generation with Diffusers

Instead of directly training on AI-generated images collected online, and compare them with the real photos from Section **??**, we used an image-to-image (image-conditioned) generation pipeline to create AI-generated images from the real photos. The reason is that we think if we cannot make sure the AI-generated images and the real photos share the same themes, styles, content or objects, the model we train could learn that a certain theme/style of pictures containing certain things are from AI or real world without actually learning the general characteristics of the AI-generated photos. To mitigate this bias in the dataset, we came up with the solution of generating variations from given real world photos, so that our AI-generated images are of the same theme, similar style and content.

Even though diffuser-based image generation models have shown great success recently and achieved state-of-the-art results in conditioned image generation benchmarks, most of them are text-conditional, which means they take texts as an input to describe the images for the model to generate. In order for us to generate new variations of given real-world photos, we utilized an image-to-image generation pipeline that is present in DALL·E 2 APIs and a similar pipeline developed by Stable Diffusion community, which utilized image encoder output as conditioning.

Diffusion models, also known as DMs, are a type of generative model that sequenctially uses denoising autoencoders to synthesize new images. By decomposing the image generation process into a series of denoising steps, diffusion models can produce high-quality images that are similar to the ones they were trained on. To generate a new image, a diffusion model takes a noisy image as input, and starts with a certain step number. Then instead of directly predicting the denoised image, it uses denoising autoencoders to predict the noise added in the previous step, and then subtract that noise from the noisy image to get a less noisy image, because noise here is mathematically easier for the model to learn to predict. Then the slightly denoised image with a new step number that is smaller by 1 is fed into the autoencoder again to continue the denoising process. This process repeats until reaching step 1 where we have our final image.

3.2.1 CLIP guidance

CLIP (Contrastive Language-Image Pre-Training) is a neural network that has been trained on a large collection of (image, text) pairs. It has both an image encoder and a text encoder, and the goal of the model is to learn a representation of the images and texts that maximizes the cosine similarity between the representations of matching pairs (**?**). As a result, CLIP model gives a great way to encode texts into vectors as embeddings, which is used in diffusion models like DALL·E 2 and Stable Diffusion to guide the image generation process so that the generated images fit the given texts. For every step of the diffusion process, the text encoder output from the CLIP model is used as image embedding into the denoising autoencoder to guide it to clear up noise. That way, the generated images are more likely to fit the description of the given texts, when the texts are used as conditioning.

A similar approach is to use the image encoder output from the CLIP model as image embedding into the denoising autoencoder. This is the approach we used in our project. We used the image encoder output from the CLIP model as image embedding into the denoising autoencoder to guide it to clear up noise. This way, the model appears to generate variations of the given image that are similar to the them.

3.2.2 Stable Diffusion

Stable Diffusion is one of the text-to-image models released in 2022 and is a latent diffusion model, a variety of deep generative neural network developed by the CompVis group at LMU Munich (**?**). It combines the advantages of powerful pretrained autoencoders and diffusion models, which are sequential applications of denoising autoencoders, to achieve state-of-the-art synthesis results on image data and beyond. Since Stable Diffusion is the only open-source one among the 3 most popular diffusion models and it is designed to reduce computational requirements while retaining visual fidelity can run on most consumer hardware equipped with a modest GPU, we can run it on Google Colab to generate part of our main dataset while paying no licensing fee for the model.

3.2.3 DALL·E 2

DALL·E 2, on the other hand, is a similar text-to-image generative model that also uses a diffusion model conditioned on CLIP image embeddings, and is developed by OpenAI as commercial product providing inference API services (**?**). DALL·E 2 is trained on a large collection of proprietary captioned high-quality stock images other than scraped images from the internet like Stable Diffusion. As a result, DALL·E 2 is capable of generating more intricate and sophisticated images than Stable Diffusion or Midjourney, which is another closed-source Diffusion model that is more known for its artistic style. DALL·E 2 comes with a image variation generation API which, under the hood, uses the image encoder from CLIP to condition the diffusion model, similar to what we use with Stable Diffusion. Because of our limited budget, we cannot afford to use DALL·E 2 to generate our main dataset, but we can use it to generate two small datasets for validation.

3.2.4 Image Variation Generation

3.3 Processed Datasets

4 ResNet Classifier

The main task of this project is classification. Over the years, researchers tend to make deeper neural networks(adding more layers) to solve such complex tasks and to also improve the classification accuracy. But, it has been seen that as we go adding on more layers to the neural network, it becomes difficult to train them and the accuracy starts saturating and then degrades also. Therefore, we decided to use ResNet, which overcomes the above issue, to do the classification.

ResNet, short for Residual Network, provides another way for data to reach later regions of the neural network by skipping some layers. Consider a series of layers, from layer I to layer $I + n$, and the function F that these layers represent. Layer i's input is denoted by x. x will simply run through these layers one by one in a classic feedforward arrangement, and the result of layer $I + n$ is $F(x)$.

The Resnet conducts element-wise addition $F(x) + x$ after applying identity mapping to x. A residual block or a building block is the term used in literature to describe the entire architecture that takes an input x and creates an output $F(x) + x$. An activation function, such as ReLU applied to $F(x)+x$, is frequently included in a residual block.

The advantage of adding this type of skip connection is that if any layer hurt the performance of architecture then it will be skipped by regularization. So, this results in training a very deep neural network without the problems caused by vanishing/exploding gradient.The training process of a neural network with residual connections has been proven to converge significantly more readily.

5 Experiments

5.1 Experiment Settings

As discussed in the previous section, the classification model is Resnet34 integrated inside the fastai. About the dataset:

5.1.1 Training

We split around 80% of the Indoor Scene Recognition Dataset with its generated pictures (using Stable Diffusion) for the training part.

5.1.2 Validation

We split around 20% of the Indoor Scene Recognition Dataset with its generated pictures (using Stable Diffusion) for the validation part. The validation data is not used in the training process.

5.1.3 Testing

The testing dataset includes several types of pictures:

Stable Diffusion model

Weather Image Recognition Dataset: real-world weather pictures with their generated pictures.

Comic Books Images Dataset: comic book images with their generated pictures.

Dalle2 model

Weather Image Recognition Dataset: real-world weather pictures with their generated pictures.

5.2 Evaluation Metrics

To evaluate the performance of the model, we used accuracy, precision, recall and F1-score as evaluation metrics. Below are the formulas for calculating the accuracy, precision, recall and F1-score. Here we assume the AI-generated pictures as positive labels while original pictures as negative labels. Thus, TP is the number of AI pictures being correctly predicted as AI pictures, FP is the number of original pictures being wrongly predicted as AI pictures. Similarly, TN is the number of original pictures being correctly predicted as original pictures, FN is the number of AI pictures being wrongly predicted as original pictures.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

6 Experiment Results

Experiment results go here.

7 Conclusion

Conclusion goes here.

8 Discussion and Future Work

Discussion and future work go here.

References

Figure 4: Validation Confusion Matrix