Deblurring Faces with a GAN: Improving Facial Recognition and Security through Neural Networks

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Abstract

The project involved the use of a Generative Adversarial Network (GAN) to unblur blurred faces. The training data was generated by obtaining an external face dataset and blurring the faces to generate the pairs of blurred and unblurred faces. Tensorflow was used to create and train the neural network. This network has several potential implications in society, including improved facial recognition technology and the ability to restore faces in blurry images.

Introduction

In this paper, we present a method for deblurring faces using a Generative Adversarial Network (GAN). We chose to focus on this problem because of the potential applications of improved facial recognition technology and the current limitations of existing deblurring methods.

Motivations

The motivations for this project are threefold. Firstly, we wanted to explore the capabilities of GANs in image restoration tasks, as GANs have shown great success in generating high-quality images in other contexts. Secondly, we are interested in improving facial recognition technology, as accurate facial recognition has many potential applications in fields such as security and surveillance. Finally, we believe that our method has the potential to be useful in restoring faces in blurry images, which could be valuable in a variety of contexts, such as improving the quality of security camera footage.

Ethics

We recognize that this technology has the potential to raise concerns about personal privacy if it is used without proper oversight. Therefore, it is important to consider the ethical implications of using GANs for deblurring faces, and to ensure that any applications of this technology are used responsibly.

One of the main ethical concerns surrounding the use of GANs for deblurring faces is the potential for this technology to be used to violate individuals' privacy. Potential solutions to this concern include obtaining explicit consent from individuals before using the technology on their images, developing technical safeguards to prevent unauthorized use, and considering the broader societal implications of using this technology. It may be necessary to establish regulations or guidelines to ensure that the technology is used in an ethical and responsible manner.

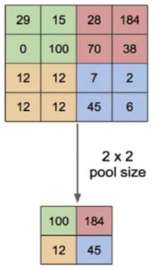
Preprocessing

We preprocess images for training a neural network by resizing them to a constant size and normalizing the pixel values to be between -1 and 1. We may also add noise and random transformations to the images to make the training data more diverse. These preprocessing steps help us prepare the images for training and improve the network's performance.

672 x 672 256 x 256

Downsampling & Upsampling

Upsampling is the process of increasing the resolution of images generated by the generator in a GAN, while downsampling is the process of decreasing the resolution of images fed into the discriminator. These processes allow the generator and discriminator to operate at different scales, providing layers of context to areas of an image, and improve the overall performance of the network.

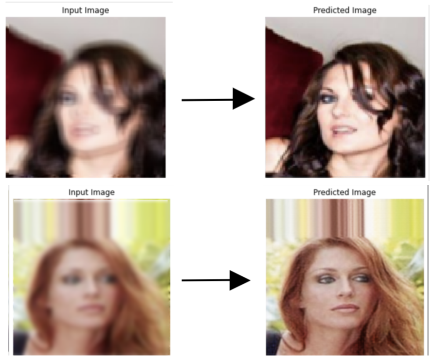


GAN: Discriminator & Generator

The discriminator and generator are two neural networks that work together to generate new data. The discriminator is trained to classify images as either real or fake, while the generator produces synthetic images that are intended to fool the discriminator. As the generator becomes better at producing realistic images, the discriminator must become better at distinguishing real from fake. This "dance" back and forth allows the GAN to generate new data that is strikingly similar to the original dataset.

Results

Given a blurred face, the model is able to generate a "predicted" image wherein it attempts to "unblur" the face. On the right we can see a few examples.



Conclusion

One of the key positive aspects of the GAN model is that it was able to produce very realistic looking unblurred faces from blurred input images. The results of our experiments show that the model was able to effectively deblur faces, resulting in high-quality images that closely resembled the original, unblurred faces. Additionally, the use of a validation data set allowed the model to be tested on unseen images, which showed that it was able to generalize well to new data. This suggests that the model has the potential to be used in a variety of real-world applications, such as improving the quality of security camera footage or restoring blurry personal photographs.

However, it is worth noting that the model did not perform as well on images that were drastically different than the style of the face dataset used to train it. This suggests that further work may be needed to improve the model's ability to handle a wider range of image styles. This could involve using a more diverse training dataset, or developing new techniques to allow the model to adapt to different styles of images more effectively. Overall, our results show that GANs have the potential to be a valuable tool for deblurring faces, but there is still room for improvement in terms of the model's generalization ability.

References

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