Image Upscaling Using AI

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Abstract- High Resolution displays has reached too far till the Human eye limit and has become more widespread and accessible to everyone than ever before, and that single hand-edly increased the importance of the Image Quality. Though, being most of the Image Compression algorithms used by the Internet are lossy, these displays may not be able to secure the high quality contents necessary to please the human eyes. And at this end, We are using the recent AI advancements like Generative Adversarial Networks(GAN) to solve this situation. The Progressive GAN approach as projected, is able to achieve high performance to quality ratio and we are working on making it accessible to everyone for free over the internet. We are also planning to leverage this to make high quality image transfer possible over the internet, using less data, through an instagram like image sharing platform

I. Introduction

Everyday the web is used to share and store millions of pictures, enabling one to explore the world, research new topics of interest, or even share a vacation with friends and family. However, many of these images are either limited by the resolution of the device used to take the picture, or purposely degraded in order to accommodate the constraints of cell phones, tablets, or the networks to which they are connected. With the ubiquity of high-resolution displays for home and mobile devices, the demand for high-quality versions of low-resolution images, quickly viewable and shareable from a wide variety of devices, has never been greater.The widespread availability of high resolution displays and rapid advancements in deep learning based image processing has recently sparked increased interest in super resolution. In particular, approaches to single image super resolution (SISR) have achieved impressive results by learning the mapping from low-resolution (LR) to high resolution (HR) images based on data. Typically, the upscaling function is a deep neural network (DNN) that is trained in a fully supervised manner with tuples of LR patches and corresponding HR targets. DNNs are able to learn abstract feature representations in the input image that allow some degree of disambiguation of the fine details in the HR output

we propose a method that is progressive both in architecture and training. We design the network to reconstruct a high resolution image in intermediate steps by progressively performing a 2X upsampling of the input from the previous level.As building blocks for each level of the pyramid, we propose dense compression units, which are adapted from dense blocks to suit super-resolution. Compared to existing progressive SISR models , we improve the reconstruction accuracy by simplifying the information propagation within the network; furthermore we propose to use an asymmetric pyramidal structure with more layers in the lower levels to enable high upsampling ratios while remaining efficient

II. Literature Survey

1.Photo-Realistic Single Image Super-Resolution Using a Generative AdversarialNetwork

This paper propose a perceptual loss function which consists of an adversarial loss and a content loss. The adversarial loss pushes our solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images. In addition, we use a content loss motivated by perceptual similarity instead of similarity in pixel space. Our deep residual network is able to recover photo-realistic textures from heavily downsampled images on public benchmarks. An extensive mean-opinion-score (MOS) test shows hugely significant gains in perceptual quality using SRGAN. The MOS scores obtained with SRGAN are closer to those of the original high-resolution images than to those obtained with any state-of-the-art method.This paper propose a super-resolution generative adversarial network (SRGAN) for which we employ adeep residual network (ResNet) with skip-connection and diverge from MSE as the sole optimization target.Neighborhood embedding approaches upsample a LRimage patch by finding similar LR training patches in a lowdimensional manifold and combining their corresponding HR patches for reconstruction

2.RAISR: Rapid and Accurate Image Super Resolution

With RAISR, we instead use machine learning and train on pairs of images, one low quality, one high, to find filters that, when applied to selectively to each pixel of the low-res image, will recreate details that are of comparable quality to the original. RAISR can be trained in two ways. The first is the ”direct” method, where filters are learned directly from low and high-resolution image pairs. The other method involves first applying a computationally cheap upsampler to the low resolution image and then learning the filters from the upsampled and high resolution image pairs. While the direct method is computationally faster, the 2nd method allows for non-integer scale factors and better leveraging of hardware-based upsampling.Upsampling, the process of producing an image of larger size with significantly more pixels and higher image quality from a low quality image, has been around for quite a while. Well-known approaches to upsampling are linear methods which fill in new pixel

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values using simple, and fixed, combinations of the nearby existing pixel values. These methods are fast because they are fixed linear filters. But what makes these upsampling methods fast, also makes them ineffective in bringing out vivid details in the higher resolution results. As you can see in the example below, the upsampled image looks blurry – one would hesitate to call it enhanced.

III. OBJECTIVES AND SCOPE OF WORK

Super-resolution technology, using one or many frames, has come a long way.The use of machine learning, in tandem with decades of advances in imaging technology, has enabled progress in image processing that yields many potential benefits. For example, in addition to improving digital "pinch to zoom" on your phone, one could capture, save, or transmit images at lower resolution and super-resolve on demand without any visible degradation in quality, all while utilizing less of mobile data and storage plans.The image scaling using Artificial Intelligence is aimed to enhance the images that are having low resolution to a better one with the help of some training algorithms like Generative adversarial network(GAN).This model can be used in aerial surveillance ,so we can easily find out the unmanned aerial vechicle or spy plane.we can also use this in medical diagnosis.This model can be used to make high quality image transfer possible over the internet, using less data.

IV. PROPOSED SYSTEM

High Resolution displays have become more accessible to every one and that increased the important of image quality.A solution to the problem of training stable GAN models for larger images is to progressively increase the number of layers during the training process.Our proposed model use a method (ProSR) that is progressive both in architecture and training: the network upsamples an image in intermediate steps, while the learning process is organized from easy to hard, as is done in curriculum learning. To obtain more photorealistic results, we design a generative adversarial network (GAN), named ProGanSR, that follows the same progressive multi-scale design principle. This not only allows to scale well to high upsampling factors (e.g.,
8) but constitutes a principled multi-scale approach that in-creases the reconstruction quality for all upsampling factors simultaneously.Compared to the top-ranking team, our model is marginally lower, but runs 5 times faster.GANs provide a powerful framework for generating plausible-looking natural images with high perceptual quality. The GAN procedure encourages the reconstructions to move towards regions of the search space with high probability of containing photo-realistic images. Early approaches upscale the LR image in a preprocessing step. Thus, the CNN learns to deblur the input image. However, this requires the network to learn a feature representation for a high-resolution image which is computationally expensive. To overcome this limitation, many approaches opt for operating on the low dimensional features and perform upsampling at the end of the network via sub-pixel convolution [30] or transposed convolution. In the case of ProGANSR the the upscaling is done by a pyramidal process. A pyramidal decomposition of u into a series of simpler functions u0,...,us. Each function or level is tasked with refining the feature representation and performing a 2 upsampling of its own input. Each level of the pyramid consists of a cascade of dense compression units (DCUs) followed by a sub-pixel convolution layer.This algorithm operate in a content aware manner.

V. METHODOLOGY

In this proposed system,the image upscale en-gine will take the low quality input image then it will be passed according to the quality needed by the user.Different levels of upscaling are available based on the performance and quality needed. Models are written in PyTorch as a pipeline.The ProGAN algorith is used in it.Progressive Growing GAN is an extension to the GAN training process that allows for the stable training of generator models that can output large high-quality images.It involves starting with a very small image and incrementally adding blocks of layers that increase the output size of the generator model and the input size of the discriminator model until the desired image size is achieved.Progressive Growing GAN requires that the capacity of both the generator and discriminator model be expanded by adding layers during the training process.This is much like the greedy layer-wise training process that was common for developing deep learning neural networks prior to the development of ReLU and Batch Normalization.Progressive Growing GAN involves using a generator and discriminator model with the same general structure and starting with very small images, such as 44 pixels.The incremental addition of the layers allows the models to effectively learn coarse-level detail and later learn ever finer detail, both on the generator and discriminator side.This incremental nature allows the training to first discover large-scale structure of the image distribution and then shift attention to increasingly finer scale detail, instead of having to learn all scales simultaneously.During training, new blocks of convolutional layers are systematically added to both the generator model and the discriminator models.Models takes low res content at one end and returns at the other end.

VI. REQUIREMENTS

Description and priority

Flask is a web framework,it is a Python module that lets you develop web applications easily. It's has a small and easy-to-extend core.

PyTorch is an open source machine learning library based on the Torch library,used for applications such as computer vision and natural language processing.models are witten in pytorch.

Google Cloud Platform (GCP)- Offered by Google, is a suite of cloud computing services that runs on the same infrastructure that Google uses internally for its end-user products, such as Google Search, Gmail and YouTube.[1] Alongside a set of management tools, it provides a series of modular cloud services including computing, data storage, data analytics and machine learning.

VII. Conclusion

A content aware and efficient Image upscaler to help reduce the data usage, increase the image details and to provide better content to the innovative display technologies, while staying within the constraints of computational power available.This model aims to provide high quality image from low quality image within a short time.It is capable of improving every field that depends on images including medical image processing,surveillance

VIII. Reference

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