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An Approach for Damaged Facial Image Restoration using GAN

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Abstract
Deep learning has evolved as the fastest emerging machine learning technique in the field of Image processing. The development of deep learning algorithms such CNN, RNN, GAN etc. have made possible in solving many image related problems such as recovering damaged image, image implanting's, increasing the Resolution of image and so on. Aiming at achieving good restored facial image, a method of applying a known value to distorted part of image from its surrounding rather than noise based on GAN can be viewed in this paper. Firstly, a GAN model is trained with facial image data sets which include facial part of celebrity from all over the world. Secondly, a masked different facial parts image is provided to check the ability of trained model to generate the portion of masked part. The GAN network mainly consist of generator and discriminator working together to carry out the task of filling the distorted part of image with some real one.

Keywords
GAN, CNN, image restoration, image repair

1. Introduction

Images have huge interaction on day to day lives from sharing historical memories to recording current state of day to day life events. Due to various reasons such as fading, creasing, staining and tearing e.t.c images gets damaged as it gets older with time. Image restoration technique is one of the widely used computer vision task of recovering the damaged part of the image.From the past ten years the research for restoring damaged image using machine learning platform has been going on applying different techniques and methods.

Within this decade, image restoration research has been conducted by utilizing the historical research papers in solving restoration task. One of the most widely researched techniques in this field is use of Generative Adversarial Network (GAN) in restoring or generating the missing parts of damaged image. Different research are being conducted on restoring the facial part of image.This paper also deals with restoring facial parts such as eye, nose, leaps etc.

2. Research Objective

The main objective of the research is to use a Deep learning method that self-generates recovered facial part from damaged image as input and compare the resultant output with the symmetrically cropped image from the undamaged part to damaged part of the image.

3. Literature Review

Few years back, before the charm of deep learning the task of image processing was tedious. The process of feature extraction, their inspection and manipulation, analysis of image content has been made easy with advancement in deep learning. Deep learning has enhanced the possibility of things that was achievable in the field of Digital Image Processing.[1]

Lehtinen [2] applied statistical reasoning to reconstruct the signal by machine learning algorithm from which it was possible for algorithm to learn to restore image from the Damaged images or corrupted images. It can be seen the approach has removed photographic noise and reconstructed the under sampled MRI scans.

Tagare [3] has explored the difference between the nature of text and image with their effects on the design of the medical image database trying to enable content based indexing and retrieval.

Pathak [4] applied an unsupervised visual feature learning technique enhanced by context-based pixel prediction method. The Context Encoders is a convolutional neural network trained to generate the contents of an arbitrary image area conditioned on its nearby features and in order to succeed the task, context encoders used the content of the total image and produce a plausible hypothesis for the missing parts. Also this paper found that a context encoder learns a representation that captures not just appearance but also the semantics of visual structures.

Liu [5] proposed a Deep Regulated Convolutional Network (RC-Net), a deep network composed of regulated sub-network blocks cascaded by skip-connections, to overcome bottleneck. It has applied both large and small convolution filters balancing the effectiveness of prominent feature extraction and the generalization ability of the model. RC-Nets outperform state-of- the-art approaches with large performance gains in various image restoration tasks while demonstrating promising generalization ability.

Ulyanov [6] has shown that, the architecture of a generator network is enough to capture a great deal of low-level image statistics prior to any learning also randomly started neural network can be used as a handcrafted prior with excellent results in standard inverse problems such as DE noising, super-resolution, and impainting. This research also bridges the gap between two very popular families of image restoration methods: learning-based methods using deep convolution networks and learning-free methods based on handcrafted image priors such as self-similarity.

According to Liu [7] image impainting has a good application value in image editing, however traditional image impainting techniques cannot complete semantic repair in the case of insufficient sample resources. Deep learning neural network have powerful learning capabilities and can extract high-level semantic features. These features can be used to semantically fill missing regions. Ideal image restoration needs to maintain structural consistency and texture clarity.

Javed [8] used an image processing technique to conceal identities of sensitive objects. It recovers the mosaiced parts in an image, especially focusing on facial parts. The paper have evaluated their method on the CelebA dataset and achieved better results than state-of-the-art image completion methods without explicitly exploiting the location information of mosaiced parts.

Wang et al. [9] have shown image impainting model DFG-GAN, which can effectively alleviate the artifacts problem when the missing region area is too large. Unlike other image impainting models, this model can transfer the image impainting task into a GAN task when the mask fills the total image. Apart from that, it has also taken advantage of the extra class label information to tell what kind of the damage the image have.

Murugan [10] have suggested to develop an intelligence framework to recover the possible information presented in the original scene of image. This paper provides a framework based on conditional-GAN to recover the information from the heavily damaged images. Learning parameter of the cGAN is optimized by multi-component loss function that includes improved Wasserstein loss with regression loss function.

Peng [11] focuses a face de-morphing generative adversarial net- work (FD-GAN) to restore the accomplice's facial image. It has utilized the symmetric dual network architecture and two levels of restoration losses to separate the identity feature of the morphing accomplice. It has great potential to be applied for tracing the identity of face morphing attack's accomplice in criminal investigation and judicial forensics.

Li [12] aims to repair damaged image by novel generative model-based approach, which consists of nested two Generative Adversarial Networks (GAN), the sub- confrontation GAN in generator and parent-confrontation GAN. The sub-confrontation GAN is the image generator of parent-confrontation GAN that can find the location of missing area and reduce mode collapse as a prior constraint. The parent confrontation GAN has an image generation part and a discrimination part.

Jo [13] develops an image editing system that generates images as the user provides free-form mask, sketch and color as an input. This paper has trained network with additional style loss which made it possible to generate realistic results, despite large portions of the image being removed.

By analyzing the above stated review and research paper, it can be seen the advancement in research of image restoration has been progressing Using GAN. Most of paper are trying to improve result by changing the architecture of GAN model. This paper deals with improvement in restoration of facial image using GAN by replacing random noise with predefined noise from the surrounding part of damaged image itself.

4. Methodology

Image restoration processing aims at filling the damaged part of the image with the features that make the missing part look like a real part. This conversion can be achieved using a deep learning approach which is shown in figure one.

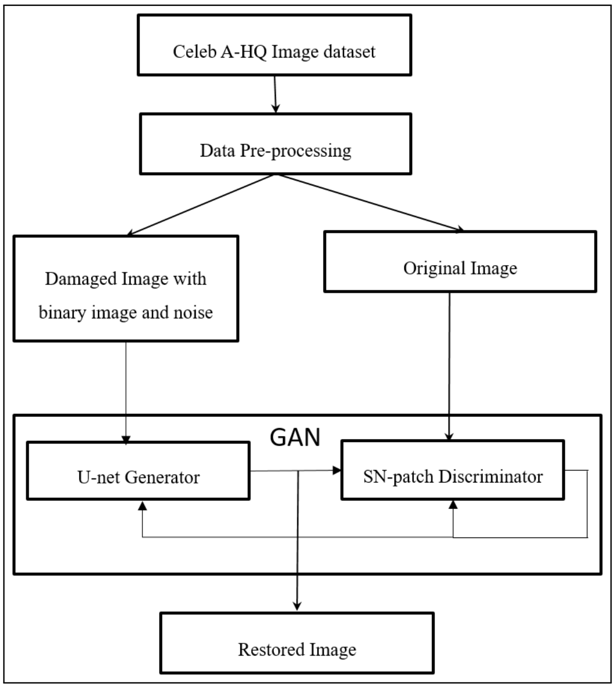

Figure 1: Proposed Approach

Image Dataset The model has implemented 20,000 Large-scale CelebFaces Attributes (CelebA) Dataset. The data set could be obtained from `http://mmlab.ie.cuhk.edu.hk/projects/CelebA.html`

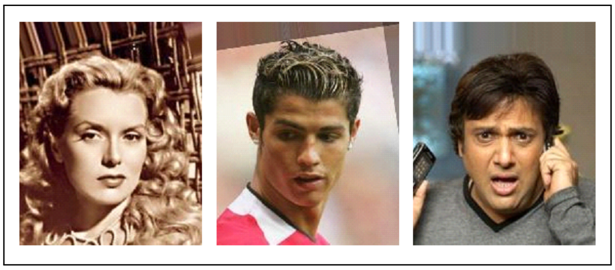

Figure 2: Sample Images from celebA Dataset

Data Preprocessing Suitable training and testing dataset is very essential for designing the model. The obtained image dataset was resized to 64 x 64 pixels. Also the task of data augmentation is also done before dividing the data into testing and training dataset.

Training Damaged Image Dataset The training datasets were used to train the learning model.The model extracts features form these training dataset from where the network learns the pattern of image. About 19,000 dataset were used to train the model. The damaged has been made by cropping the image at different level and portion.

Testing Damaged Image Dataset About 1000 image dataset was separated in advance before training of the model. After the model was trained using training dataset, the unseen test dataset was used to measure performance of the designed model. It generally helps for performance evaluation of model.

U-net GAN model selection Recently, Generative adversarial network are finding high emphasis in supervised, semi supervised and unsupervised learning vision tasks as the generative models implicitly learn probability density of high dimensional distributions of the data and generate natural looking images.The U-net structure of generator has been implemented which is the reason for GAN model to be named as U-net GAN model.

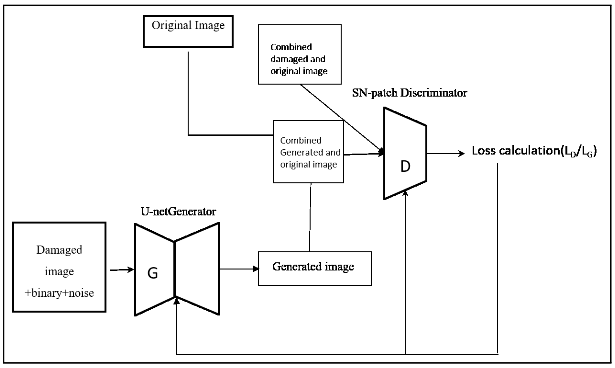

Figure 3: GAN Model

The generator and the discriminator in the GAN network competing each other in zero sum game to optimize the learning parameters. The schematic of the GAN network is shown in the Figure three. The generator generates images of natural looking data samples from noise input data to fake the discriminator while the discriminator tends to differentiate the generated samples from the real data. Both the forger (Generator) and the expert (Discriminator) learn simultaneously by minimize the distance between the probability distribution of real and generated data. However, while the discriminator has the access to the generated data and real data, the generator has no access to the real data distribution. The noise input data to the discriminator provide the possible information about the ground truth to distinguish between the synthetic generated data and real data distribution. The same noise data distribution is used for training the generator to produce natural looking images close to the real data with superior quality. The generator and the discriminator composed of deep convolutions layer and fully connected dense layers. Since the necessity of direct inevitable of the generator and the discriminator, the both network modules has to be continuous and differential everywhere.

The implemented architecture of generator and discriminator shown in block structure connected with each layer shown with arrow from starting to end layer can be viewed in figure four and five.

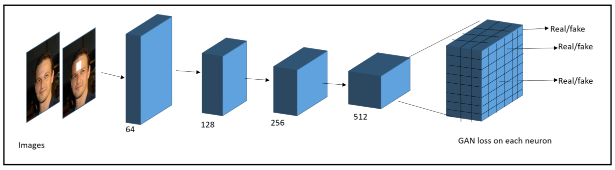

Figure 4: Discriminator architecture

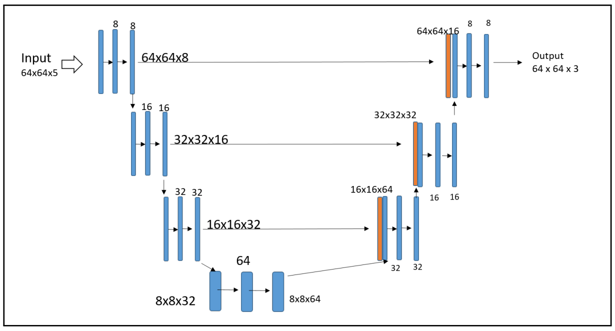

Figure 5: Generator architecture

5. Experimental setting

The model was trained on a machine having processor of Intel core Pentium i5-8400 CPU with 2.80 GHZ speed, 6 core(s), 8GB of RAM and 4GB graphics on windows operating system. The coding was conducted on python since the task of machine learning algorithm can be easily programmed as python has all libraries required for simulation. The time taken by model to train from the supplied data nearly took fourteen days.

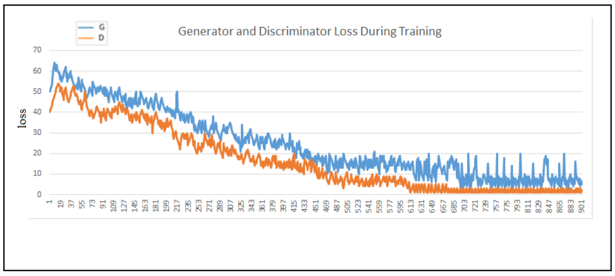

Figure 6: Loss graph of Discriminator and Generator

6. Result and Discussion

During the training of both generator and discriminator for fifty epoch , the loss value were calculated for both generator and discriminator using binary cross entropy(BCE) function.It is specially used to categories between real and fake image.The model has used BCE as the cost function.

BCE function:

$$J = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log(a^{(i)}) + (1-y^{(i)})\log(1-a^{(i)})\right] \quad (1)$$

The term $\frac{1}{m}$ represent average loss of the whole batch.The term $\log(a^{(i)})$ represents prediction made by model and the term $y^{(i)}$is the label for different examples i.e whether image is real or fake label. For eg. real could be a label of 1 and fake could be a label of 0. And $y^{(i)}$ are the features that are passed in through the prediction. The obtained graph of generator and discriminator loss can be viewed in figure six. The graph shows losses of generator and discriminator which is below over 10% till the end of 800 iteration or fifty epoch. Hence the graph shows the trained model has low loss and can be used for the objective of the work.

The output of Generator at different epoch were captured from where the progress of model to restore the damaged parts can be viewed.The some of output of Generator at different epochs are as follows:

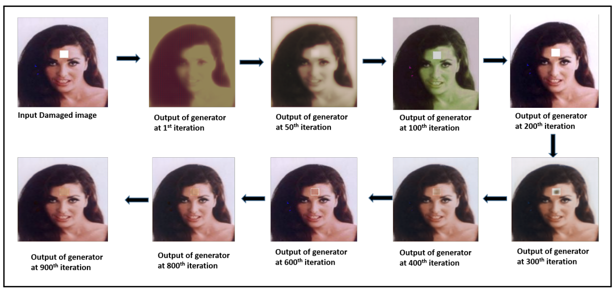

Figure 7: Generator output of damaged image

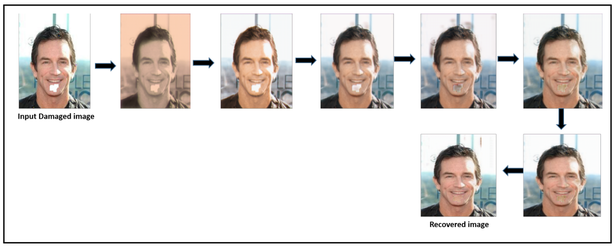

Figure 8: Generator output of damaged image

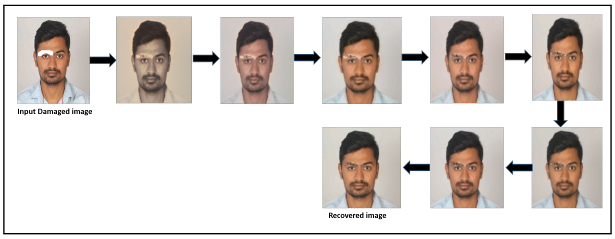

Figure 9: Generator output of damaged image

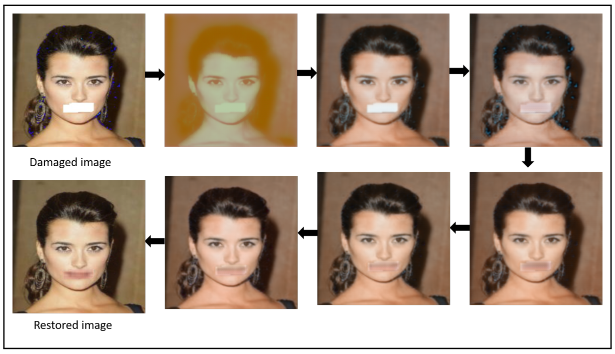

Figure 10: Generator output of damaged image

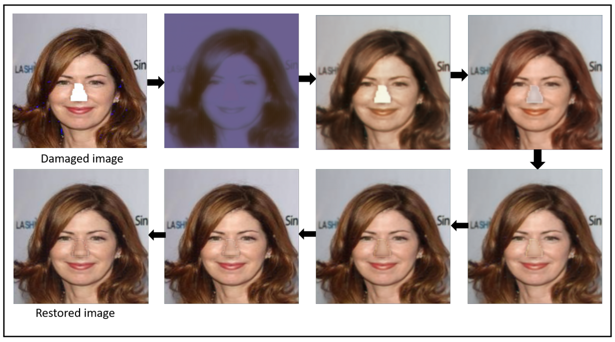

Figure 11: Generator output of damaged image

Viewing above result of generator output image with increase in number of epoch it can be concluded that the model has learned much at each steps and at the end of fifty epoch the image generated are much closer to the original image.

After the training session the testing image were provided to model which produced restored part of image. The facial portion to be regenerated were masked using mouse.Only the masked area were to be regenerate . The distortion parts were small based on different parts such as eye, nose and lips which were restored as accordingly to their location.

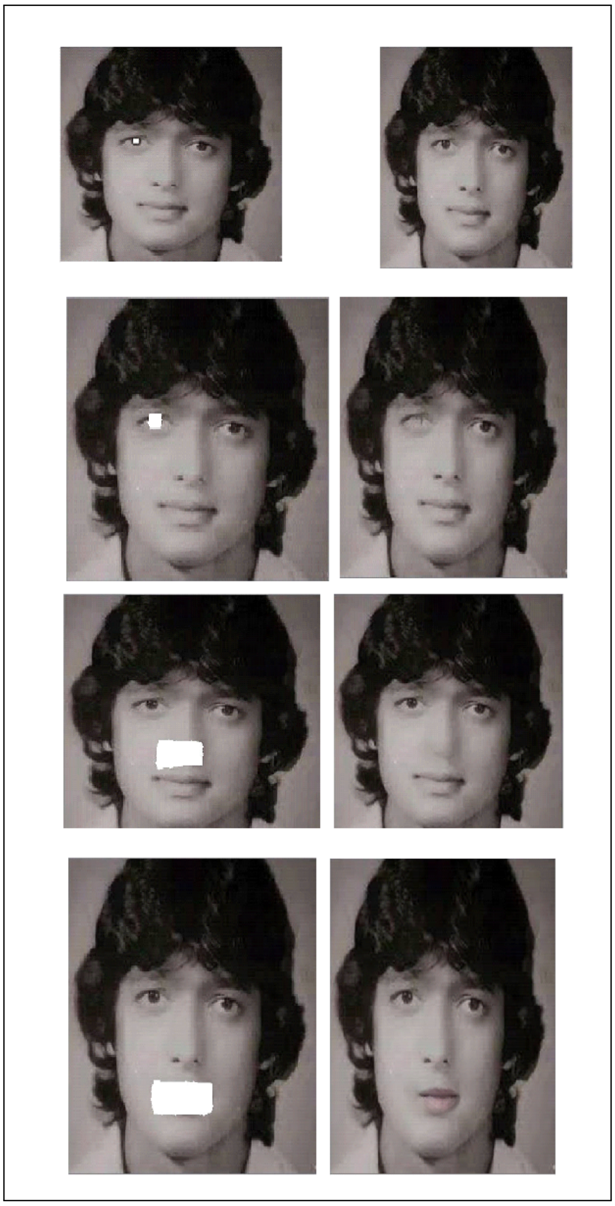

Figure 12: Model output for given damaged image

From simplicity a known image were masked so that model could generate only the area which were masked.The masked area were increased in ratio from small to large area.The restored image shows that the model has somehow restored the facial part such as eye, nose and lips.Thus the model could be implemented for recovery of small damaged portion of image.

The result were compared with Coarse-Refined structure network [13] who outputs were blurred at different stages of model development also it required huge amount of memories with the training time. This paper approached method performs better with small damaged parts as shown in figure twelve. The performance can be observed by viewing the obtained output image from the model.

7. Conclusion

GAN has become more advanced in image processing technique such as image classification, image impanting, and image restoration. With slight change in the input to the model lead to better improvement on the output of model by providing some information of image to generator rather than complete noise. As from the output image it can be concluded that model has recognized the placing area of our facial part such as eye, lips and nose.

Further research can be extended to recover any body part of human being and other animal also. Variety of noise can be experimented so that by providing different nature of noise the output of the model can be changed in accordance. Also different architecture of GAN can be tested for better improvement of generated facial image. Also the rotation of image can make a huge impact on the output image so during testing the test images could be augmented.

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