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Real Image Restoration Using VAEs

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Abstract— Old photos are an integral part of everybody's life; they remind us of how one person has spent their life. As people used hard copies of photos before, those photos suffered severe degradation. This degradation in real-time images is intricate, causing thetypical restoration that might be solved through supervised learning to fail to generalize due to the domain gap between synthetic and real images. Therefore, this method uses various autoencoders to restore and colourize old images. Furthermore, this model uses a unique triplet domain translation network on real images and synthetic photo pairs.

Precisely, VAEs, which are variational autoencoders, are trained to transform old pictures and clean pictures into two latent spaces. Therefore, the translation between these two latent spaces is comprehended with simulated paired data. This translation generalizes well to authentic images because the domain gap is encompassed in the close-packed latent space. Moreover, to manoeuvre numerous degradations present in one old picture, this model designs a world branch with a partial non-local block targeting the structured faults, like scrapes and dirt marks, and an area branch targeting unstructured faults, like noisesand fuzziness.

Two branches are blended within the latent space, resulting in an improved ability to renew old pictures from numerous defects. Additionally, it applies another face refinementnetwork to revive fine details of faces within the old pictures, thus generating photos with amplified quality. Another autoencoder is encoded with colour images, and then the decoder decodes the features extracted from the encoder. Once a model is trained, testing is performed to colourize the photographs.

Keywords— Degraded pictures, Variational Auto Encoders, Domain gap, Triplet domaintranslation.

I. INTRODUCTION

Photos are taken to capture the happy memories that are otherwise gone. Although time flies by, one can still invoke the moments of the past by watching them. However, old photo prints disintegrate when kept in poor environment, which causes the content of photo permanently damaged. Luckily, as mobile cameras and scanners become more convenient, people can now digitalize the photos and invite a talented specialist for reconstruction. However, manual retouching is typically burdensome and time-taking, which leaves stack of old photos impossible to restore. Hence, it's appealing to style automatic algorithms which can instantaneously repair old photos for people that wish to bring old photos back to life. Before the deep learning times, there are some trails that restore photos by automatically detecting the localized faults like scratches and freckles, and filling within the damaged areas with in painting process.

II. LITERATURE SURVEY

Siqi Zhang et al. [13] proposed a "unique Consecutive Context Perceive Generative Adversarial Networks (CCPGAN) for serial sections inpainting that can learn semantic information from its neighboring image and reinstate the damaged regions of serial sectioning images to the maximum extent."

Lingbo Yang et al. [12] proposed "HiFaceGAN, a collaborative suppression, and replenishment framework that works in a dual-blind fashion, reducing dependence on degradation prior or structural guidance for training."

X.Lu et al. [10] proposed a "A feed-forward image processing using CNN with multiple arbitaryholes various sizes at the time of testing."

III. METHODOLOGY

In this paper, we proposed a novel network to address the problem of old photo restoration via deeplatent space translation. We are using deep learning to restore old photos that suffered from severe degradation there are many approaches currently available but the main problem with previous conventional restoration techniques was that they were not able to generalize. This is caused becausethey are all using supervised learning which is a problem caused by the domain gap between the real old picture and the ones that are synthesized for training. There is a big difference with the synthesized old images and the real old ones. We can observe that the synthesized image is alreadyin high definition even with the fake scratches and colour changes compared to the other one that contains way less details they addressed this issue by creating their own new network specifically for the task basically they used two variational auto encoders called VAEs.

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IV. PROPOSED SYSTEM

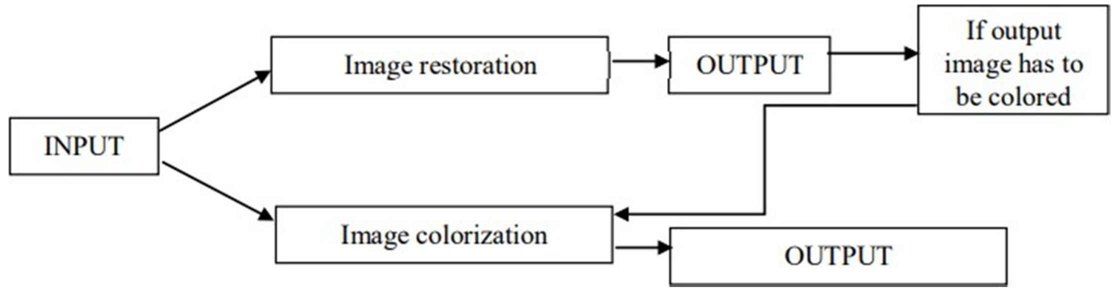
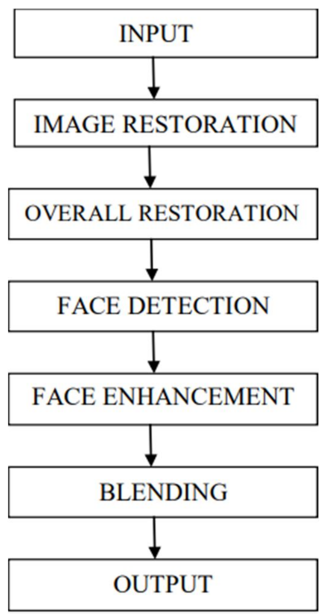


Fig. 1 Architecture of the proposed model

This model as in Fig 1 takes an image as input, if the corresponding input contains any noise or scratches, it undergoes image restoration process, if the output from the image restoration process is not coloured and if the user wants to colour the data the image is served as input for the image colorization model.

If the input does not contain any noise and does not suffer from degradation, it undergoes image colorization process and the output is shown to the user.



The further chapters in this document explains the methodology in deep

Fig. 2 Architecture of Image restoration model

The architecture of Image Restoration is as shown within the Fig 2. Before the image is restored it passes through some stages. In order to decrease the domain gap, this formulates the old photo restoration problem, where to find out the mapping in between the clean images and old photos as images are taken from distinct domains model.

V. IMPLEMENTATION

The issue with the conventional restoration techniques is addressed by creating new networkspecifically for the task basically we used two variational auto encoders called VAEs.

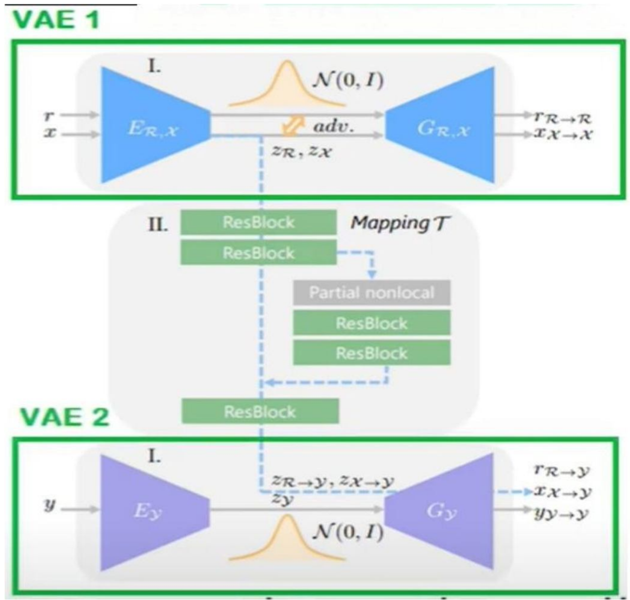


Fig. 3 The two VAEs

Fig 3 shows the two variational autoencoders VAE1 and VAE2 which respectively transform oldand clean photos into two latent spaces.

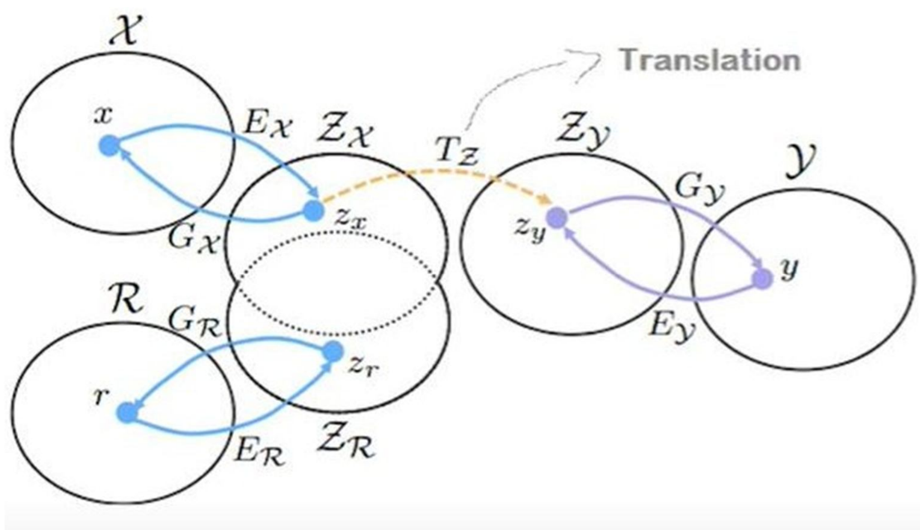


Fig. 4 Translation into latent spaces

The translation into latent spaces “Tz” (Fig 4) is learned through synthetic paired data, but is able togeneralize well on real photos since this same domain gap is way smaller on such compact latent spaces.
The domain gap from the two latent spaces produced by the VAEs is closed by training anadversarial discriminator.
From the Fig 4 we can observe that the new domains from the latent spaces, “Zx” and “Zr”, are muchcloser to each other than the original pictures “R” and synthetic old pictures “X”.
The mapping to restore the degraded photos is dome in this latent space.

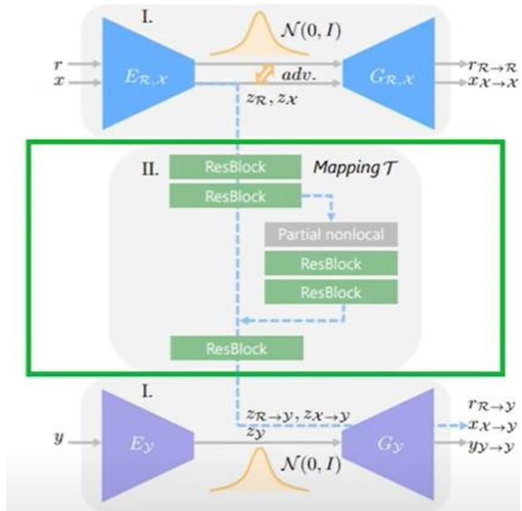


Fig. 5 Network divided into specific branches I ,II

From Fig 5 we can observe that the network is divided into specific branches that each solve aparticular problem, which they called the partial nonlocal block.

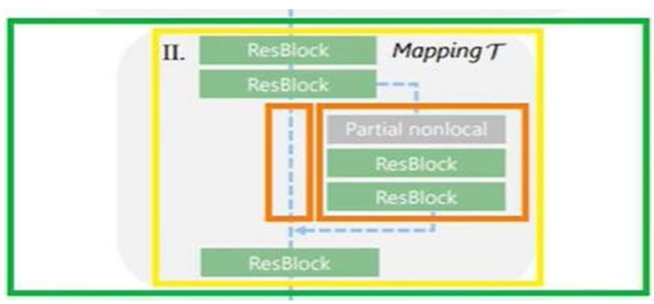


Fig. 6 Two branches

There is a global branch targeting the structured defects, such as scratches and dust spots by using a nonlocal block, considering the global context. Then they dive deeper into two local branches that target unstructured defects like noises andblurriness by using several residual blocks.

Finally, these branches are fused into the latent space that improves the capability to restore the oldphoto from all these defects.

There is one last step in order to produce even better results. Since the old photos we want to restoreare most likely pictures from our loved ones, they will always have a face in them.

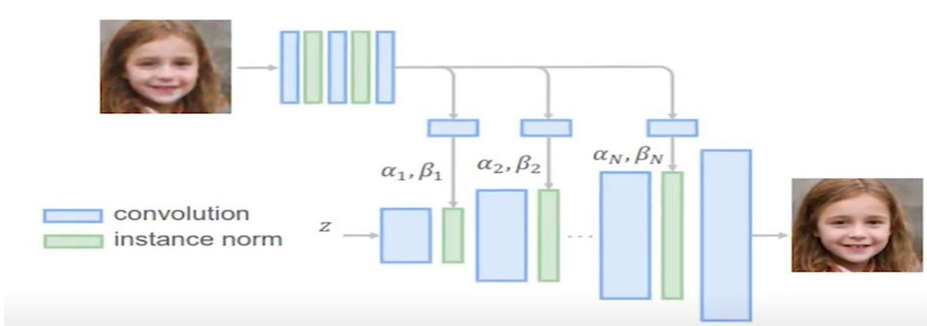


Fig. 7 Face refinement network

In order to recover the fine details of faces in the old photos from the picture in the latent space “z”(Fig 7) we have added a face refinement network, and using the degraded face into multiple regions of the network. This widely enhances the perceptual quality of the faces.

Fig. 8 Sample image for training image colorization dataset

Fig. 9 A sample image for training image colorization dataset

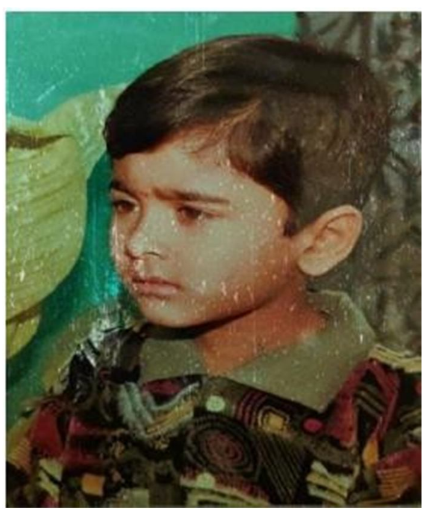


Fig. 10 A sample image that is used to test the Image Restoration model

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Fig. 11 A sample image that is used to test the Image Colorization model

VI. ALGORITHM

A. *Algorithm 1*

Algorithm 1 (for image restoration)

Input: Take input an image from user.
Step 1: Overall Restoration
All input images are processed in this stage to identify the degradation
Step 2: Face Detection
The model identifies the faces in the images.
Step 3: Face Enhancement
Face is enhanced and features are extracted. Blurness is removed. And the identifieddegradation is restored.
Step 4: Blending
Output: Outputs an image which is enhanced and removes some scratches from image.

B. *Algorithm 2*

Algorithm 2 (for image colorization)

Input: Input is Black and White image.
Step 1: Resizing images
Converting each image to a uniform size. Resizing images to 256 X 256
Step 2: Convert images from RGB to LAB
By iterating on each image, it converts the RGB channels to LAB channels.
Think of LAB image as a grey image in L channel and all colour info stored in A and B channels. The input to the network will be the L channel, so it assigns L channel to X vectorand assign A and B to Y.
Step 3: Encoder
Model=Sequential Activation function =RELUStep 4: Decoder
Model=Sequential
Activation function=RELU for 7 layers Activation function=Tanh for the 8th layerStep 5: Then the model is

trained and fitted.
Number of epochs= 300 epochs Batch size = 16 per batchOutput: Outputs coloured image.

VII. RESULTS

This model is mainly categorized into two parts i) Image restoration a) Enhancing unscratched images. b) Removing scratches and folds from photos. ii) Image colorization. This model takes input a image and outputs an image with no scratches and has a high resolution or improves colouring of image. This model is trained on 300 epochs and achieved 86%accuracy.

Fig. 12 Image Enhancement

Fig. 13 Removing some scratches and folds from photos

A. Image Colorization

1) *Accuracy:* The model in the project is checked against the accuracy measure andwe are attaining accuracy of 86% with 300 epochs.

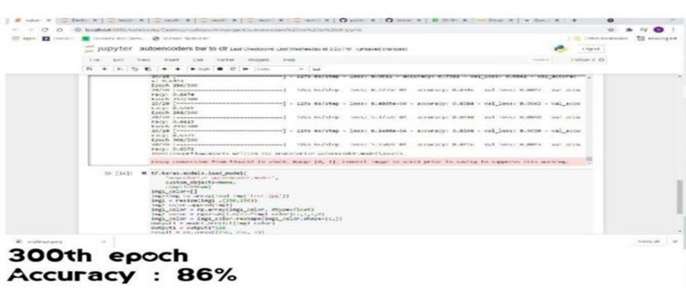

Fig. 14 Accuracy of model when trained with 300 epochs

Fig. 15 Result of an input test image for Image colorization model

Fig. 16 Result of an input test image for Image colorization model

B. *Image Restoration*

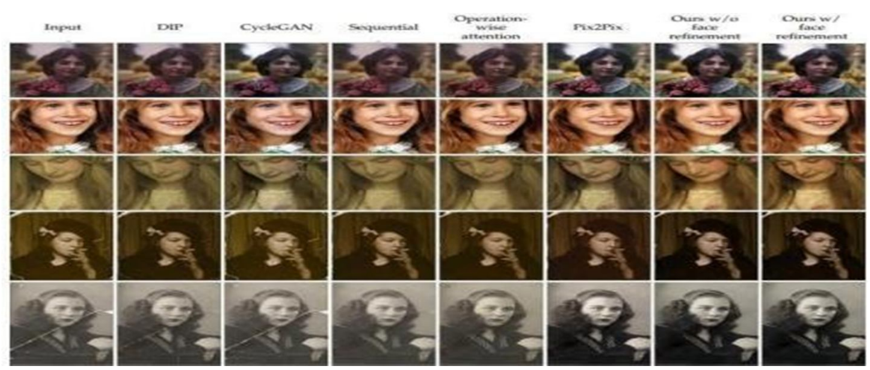

Fig. 17 Qualitative differences against state-of-the-art methods.

C. *Image Colorization*

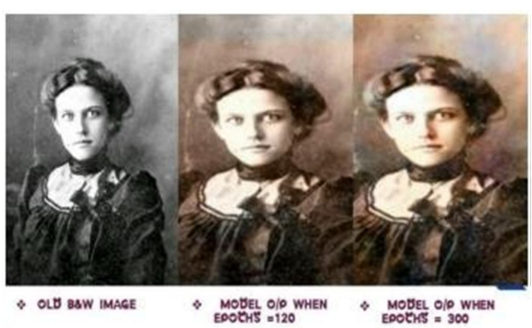

Fig. 17 Results of an input image with different number of epochs in Image Colorization model

Fig 17 shows that the amount of images coloured increased with a number of epochs. So with 300 epochs, it achieved 86% accuracy. With the increase in the number of epochs loss is reduced.

VIII. CONCLUSION AND FUTURE ENHANCEMENTS

A. Conclusion

This project concludes that the domain gap between synthetic photos and authentic old images is reduced, and latent space is used to translate to clean images. Compared with prior methods, this method suffers more minor generalization problems. Using this method, the scrapes can be in-painted with better structural consistency. To reconstruct the face areas ofold images the Coarse-to-fine generator with the spatial adaptive condition is proposed. Theblack and white images are colorized with 86% accuracy. This method displays good performance in restoring severely damaged old photographs.

B. Future Scope

Nonetheless, as the dataset used contains a few old photos with faults, this method cannot handle complex shading, which can be addressed by including more such photographs in the training network or explicitly evaluating the shading effects during synthesis.

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