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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 the typical 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 noises and 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 refinement network 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 domain translation.

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 arbitrary holes 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 deep latent 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 because they 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 already in 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.

IV. PROPOSED SYSTEM

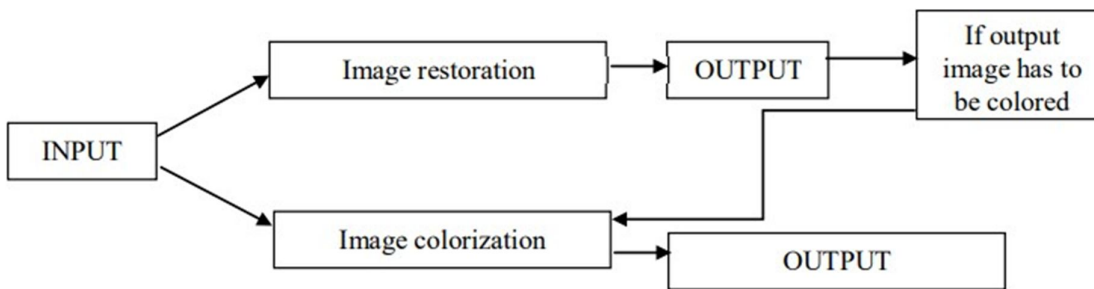
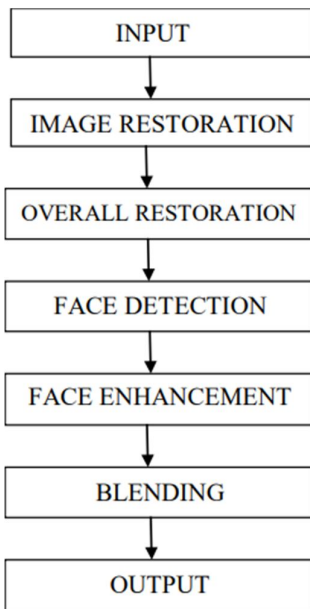


Fig. 1 Architecture of the proposed model

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 networks specifically for the task basically we used two variational auto encoders called VAEs.

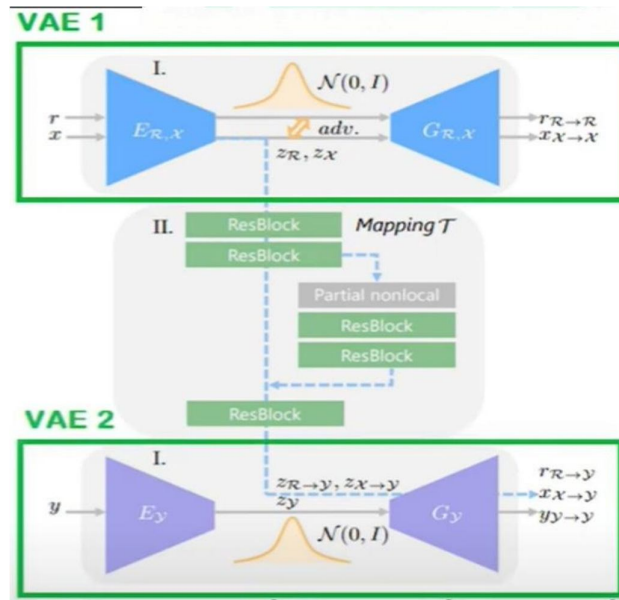


Fig. 3 The two VAEs

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

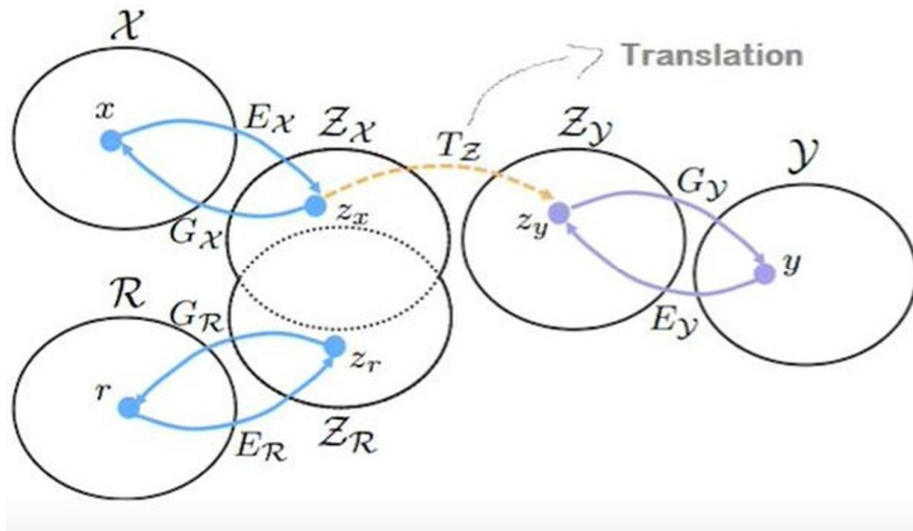


Fig. 4 Translation into latent spaces

The translation into latent spaces “ T_Z ” (Fig 4) is learned through synthetic paired data, but is able to generalize 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 an adversarial discriminator. From the Fig 4 we can observe that the new domains from the latent spaces, “ Z_X ” and “ Z_R ”, are much closer to each other than the original pictures “ R ” and synthetic old pictures “ X ”. The mapping to restore the degraded photos is done in this latent space.

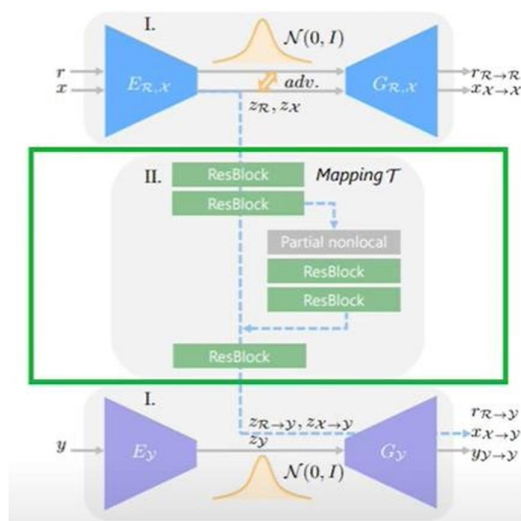


Fig. 5 Network divided into specific branches I,II

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

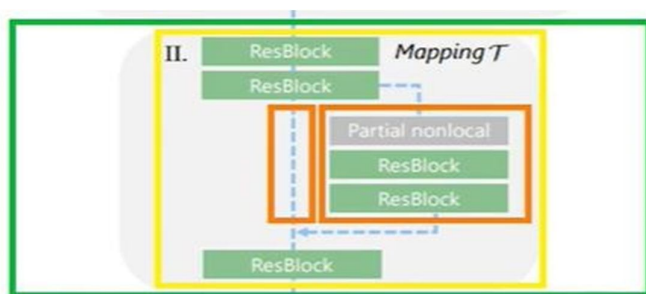


Fig. 6 Two branches

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 and blurriness by using several residual blocks.

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

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

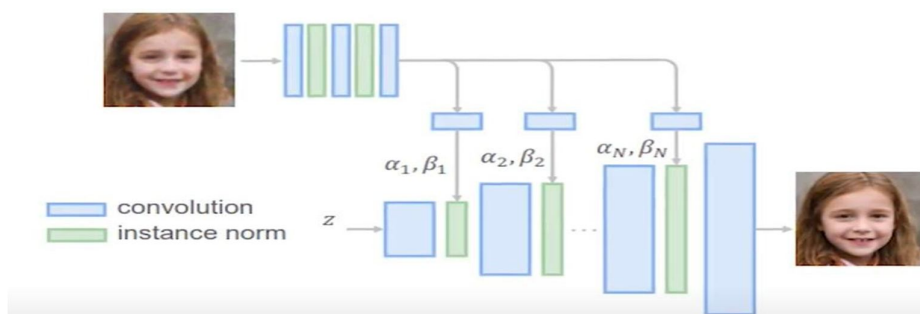


Fig. 7 Face refinement network

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

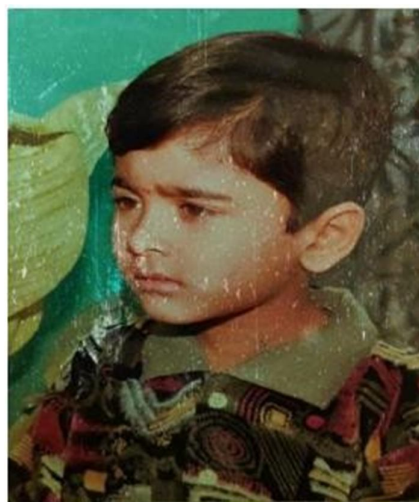


Fig. 10 A sample image that is used to test the Image Restoration model



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. Blurriness is removed. And the identified degradation 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 vector and assign A and B to Y.

Step 3: Encoder

Model=Sequential Activation function =RELU Step 4: Decoder

Model=Sequential

Activation function=RELU for 7 layers Activation function=Tanh for the 8th layer Step 5: Then the model is

trained and fitted.

Number of epochs= 300 epochs Batch size = 16 per batch
Output: 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 and we 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

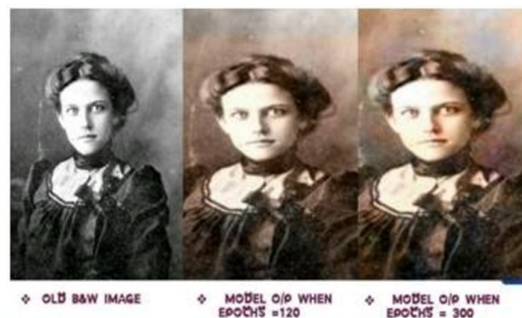


Fig. 17 Results of an input image with different number of epochs in Image Colorization model



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 of old images the Coarse-to-fine generator with the spatial adaptive condition is proposed. The black 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.

REFERENCES

- [1] H. Liu, B. Jiang, Y. Xiao, and C. Yang, "Coherent semantic attention for image inpainting," arXiv preprint arXiv:1905.12384, 2019.
- [2] L. Xu, J. S. Ren, C. Liu, and J. Jia, "Deep convolutional neural network for image deconvolution," in *Advances in Neural Information Processing Systems*, 2014, pp. 1790–1798.
- [3] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, and S. Hochreiter, "Gans trained by a two time-scale update rule converge to a local nash equilibrium," in *Advances in Neural Information Processing Systems*, 2017, pp. 6626–6637.
- [4] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, and M.-H. Yang, "Single image dehazing via multi-scale convolutional neural networks," in *European conference on computer vision*. Springer, 2016, pp. 154–169.
- [5] Y. Ren, X. Yu, R. Zhang, T. H. Li, S. Liu, and G. Li, "Structureflow: Image inpainting via structure-aware appearance flow," arXiv preprint arXiv:1908.03852, 2019.
- [6] F. Stanco, G. Ramponi, and A. De Polo, "Towards the automated restoration of old photographic prints: a survey," in *The IEEE Region 8 EUROCON 2003. Computer as a Tool.*, vol. 2. IEEE, 2003, pp. 370–374.
- [7] G. Liu, F. A. Reda, K. J. Shih, T.-C. Wang, A. Tao, and B. Catanzaro, "Image inpainting for irregular holes using partial convolutions," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 85–100.
- [8] I. Giakoumis, N. Nikolaidis, and I. Pitas, "Digital image processing techniques for the detection and removal of cracks in digitized paintings," *IEEE Transactions on Image Processing*, vol. 15, no. 1, pp. 178–188, 2005.
- [9] J. Sun, W. Cao, Z. Xu, and J. Ponce, "Learning a convolutional neural network for non-uniform motion blur removal," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 769–777.
- [10] J. Yu, Z. Lin, J. Yang, X. Shen, X. Lu, and T. S. Huang, "Generative image inpainting with contextual attention," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 5505–5514.
- [11] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising," *IEEE Transactions on Image Processing*, vol. 26, no. 7, pp. 3113–3155, 2017.
- [12] Lingbo Yang, Shanshe Wang, Siwei Ma, Chang Liu, Pan Wang, "HiFaceGAN: Face Renovation via Collaborative Suppression and Replenishment," in *Proceedings of the IEEE Conference on Computer Vision*, 2021.
- [13] Siqi Zhang¹, Lei Wang¹, Jie Zhang², Ling GU², Xiran Jhai¹, Xiaoyue Zhai², Xianzheng Shai¹, And Shijie Chang¹, "Consecutive Context Perceive Generative Adversarial Networks for Serial Sections Inpainting," in *Proceedings of the IEEE Conference on Big Data Research*, 2020.
- [14] Xiaodong Li, Xingfan Zhu, Ziyin Zhou, Qilong Sun, Qingyu Liu, "Focusing on Persons: Colorizing Old Images Learning from Modern Historical Movies," in *Proceedings of the IEEE Conference on Computer Vision*, 2021.
- [15] "Meitu," <https://www.meitu.com/en>
- [16] "Remini photo enhancer," <https://www.bigwinepot.com/index.en.htm>



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