Denoising Autoencoders for Image Quality Improvement

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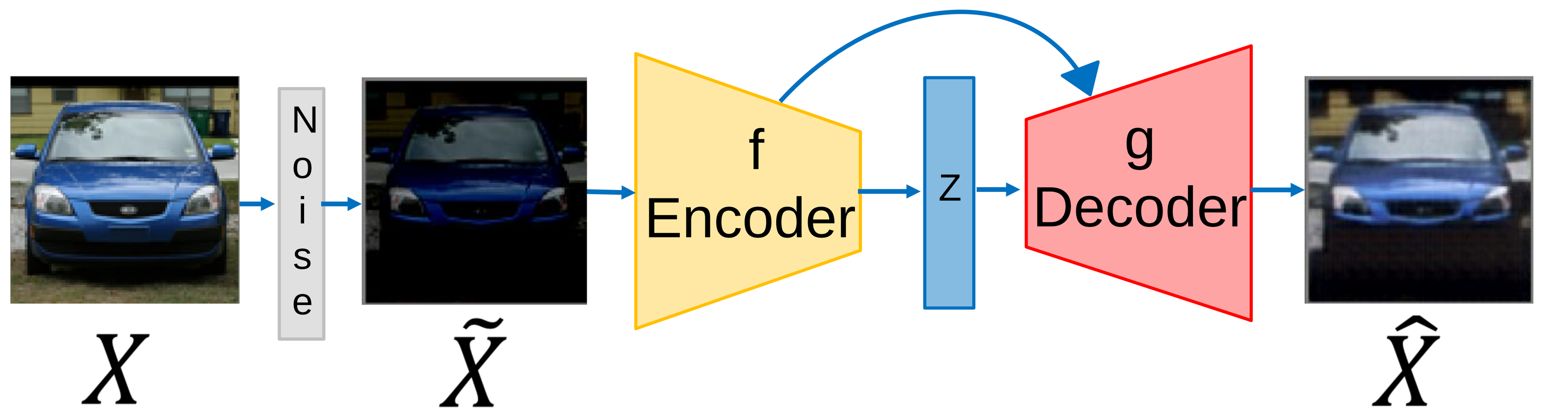
Introduction

At the Danish start-up company, Omhu, the ambition is to use machine learning algorithms to diagnose skin conditions from smartphone images taken by patients. These images however often suffer from noise such as motion blur, over- and underexposure or a combination of different types of noise. By training a denoising autoencoder to improve the quality of the images, it will be easier to classify and diagnose the patients' skin conditions from the images.

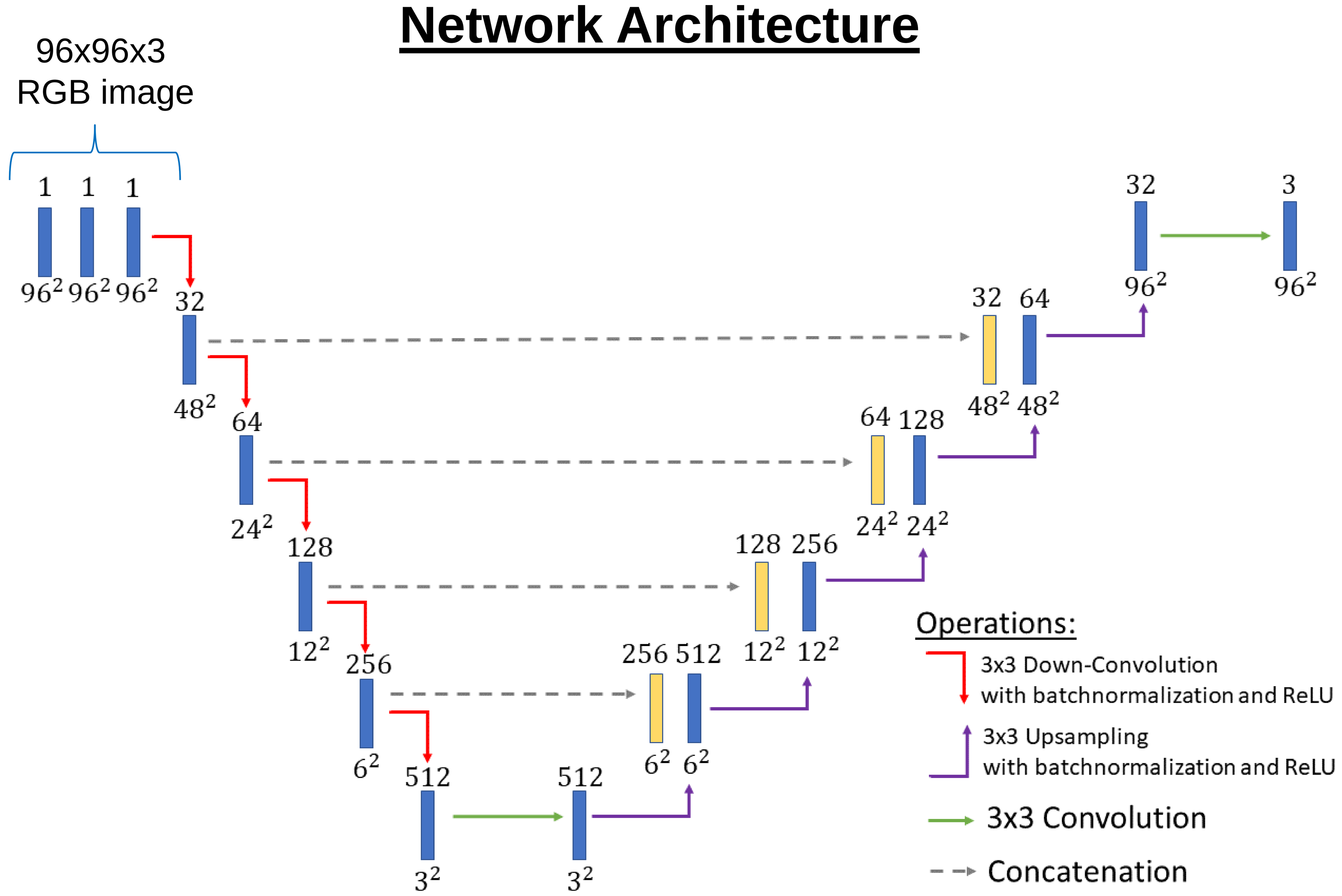
Key contributions:
- Image noise functions
- Denoising Autoencoder

Model

A Denoising Autoencoder has been selected to improve the quality of the images, as the best results were obtained using this method. A high quality image X is corrupted by applying a transformation to the image that mimics noise and the noisy image $\tilde{X}$ is then forwarded through an encoder f. The encoder reduces the dimensionality of the input to get the latent variable Z. Afterwards the latent variable is forwarded through a decoder g and the reconstruction of the high quality image $\hat{X} = g\left(f(\tilde{X})\right)$ is then compared to the original image X. The reconstruction error (MSE) is computed and the weights of the parameters are updated using the Adam Optimizer. The Denoising Autoencoder consist of a fully convolutional network.



Network Architecture



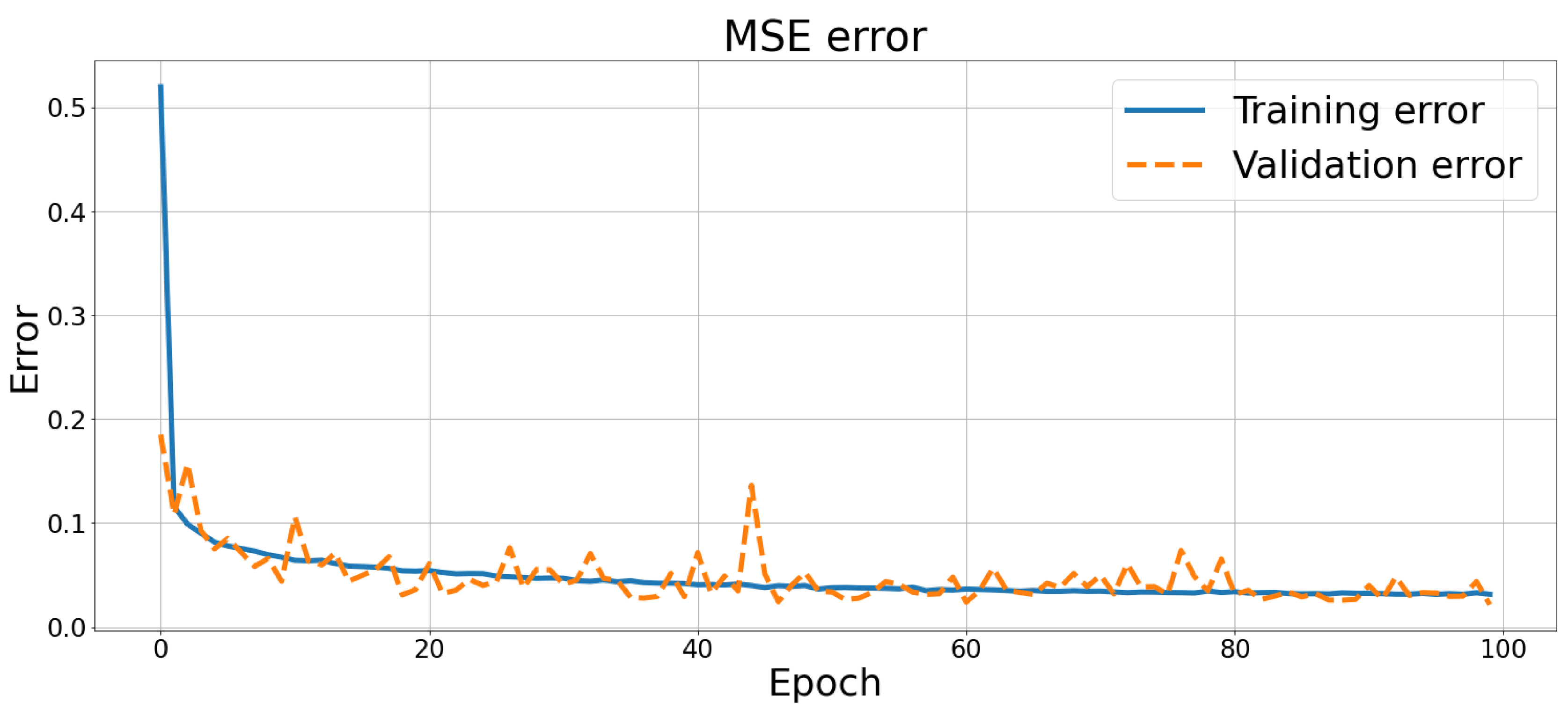
Dataset

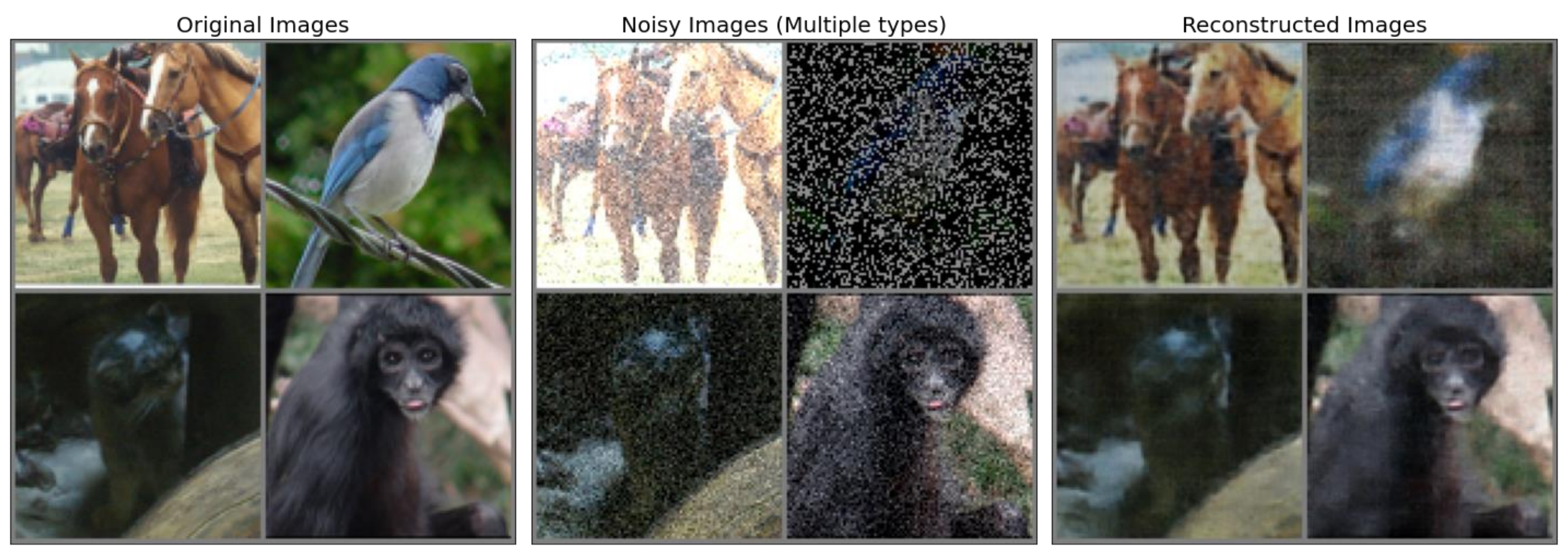
The STL-10 dataset with 8000 training images and 5000 test images of size 96x96x3 was used. The images were divided into 10 classes of equal size.

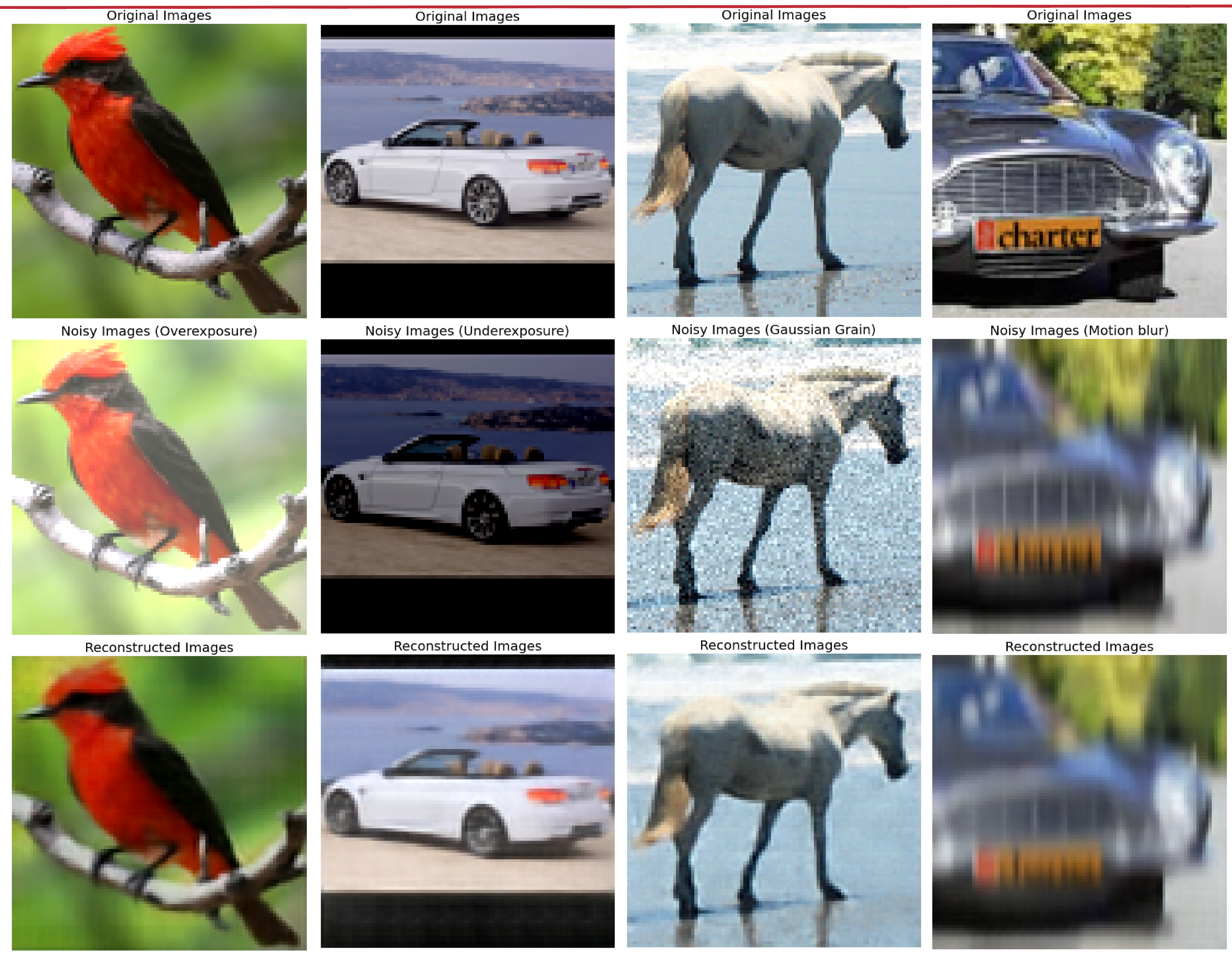
Results - Quantitative

Dataset	STL-10
# Training images	8000
# Test images	5000
Training error	0.031
Validation error	0.021

Results - Qualitative







Conclusion

It this project, it has been shown that the denoising autoencoder is able to remove different types and combinations of noise from images from the STL-10 dataset.

Future work

The next step in this process would be to train the denoising autoencoder on more challenging types of noise and image transformations such as homography transformations and resolution enhancement. With these additions, the network could be trained on the dataset containing images of patients' skin conditions. If the network denoises the images properly, the images can be correctly diagnosed.

References

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[2] T. Tong et. al. "Image Super-Resolution Using Dense Skip Connections", 16th IEEE International Conference on Computer Vision, ICCV 2017, pages 4809-4817 (2017)

[3] Adam Coates, Honglak Lee, Andrew Y. Ng "An Analysis of Single Layer Networks in Unsupervised Feature Learning", AISTATS, (2011)

[4] C. Doersch– "Tutorial on Variational Autoencoders" (2016), Carnegie Mellon/UC Berkeley

Code and Paper

The code and the paper can be accessed by scanning the QR -code