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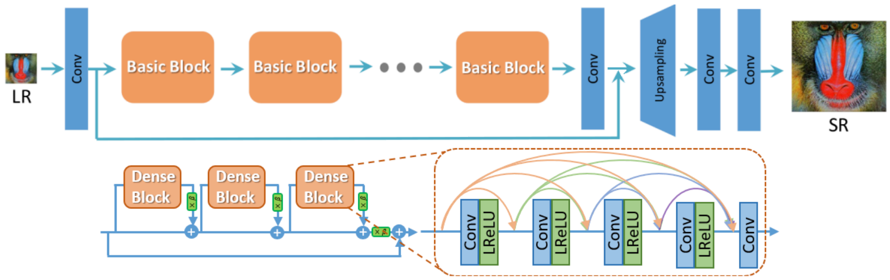
Super-Resolution GANs Transforming Satellite Imagery for Mining

Mining is a legacy industry where the exploration of natural resources has grown increasingly inefficient due to slow adoption of modern technologies. As natural resource deposits become harder to find, mining companies that innovate effectively can secure a significant competitive advantage. An example is KoBold Metals, who disrupted the market with new AI and ML uses, receiving a valuation of $1.13 billion. This project aims to explore the applications of novel ML models by enhancing low-resolution satellite imagery of Namibia using super-resolution GANs. By improving image resolution, I anticipate an increased effectiveness of downstream ML tasks, such as classification, that are crucial for identifying new mineral deposits.

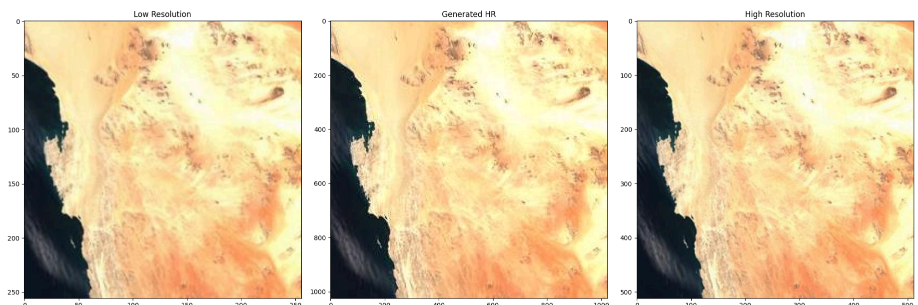
To complete this project, I sourced two different datasets. The first being a custom dataset scraped from Sentinel-2 data. This dataset consisted of 50 pairs, each pair a low-resolution and corresponding high-resolution image. The images were of random points over Namibia with a maximum of 20% cloud coverage. The low-resolution images are 128x128 and the high-resolution images are 512x512. The second dataset, Landshapes-4041, was found from a Medium post and it contains 4041 1024x1024 images of random points over the whole earth.

Initially, I trained a StyleGAN3 model from scratch using the Landshapes-4041 dataset. The objectives were to train a realistic model, encode low-resolution images into the model, and then compare the encoded images with the ground truth high-resolution images. After training for 20 hours on an A100 GPU, the results were not useful and it was clear that I did not have sufficient compute resources given the time limitation.

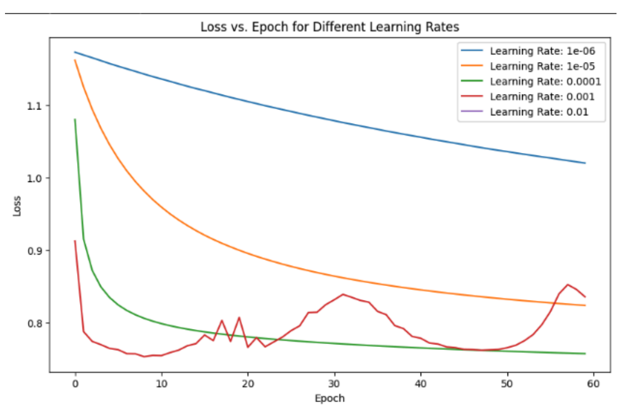
In order to improve results, I implemented the Enhanced Super-Resolution GAN (ESRGAN) to process my Sentinel-2 images of Namibia. As seen in the figure, ESRGAN, an improved version of the original SRGAN, incorporates advanced techniques like Residual-in-Residual Dense Blocks (RRDBs) which enhance detail preservation and depth when processing images. This model also omits batch normalization, allowing the model to retain more complex textures. Additionally, ESRGAN uses a perceptual loss function based on a pretrained VGG network that emphasizes perceptual similarity over pixel accuracy.



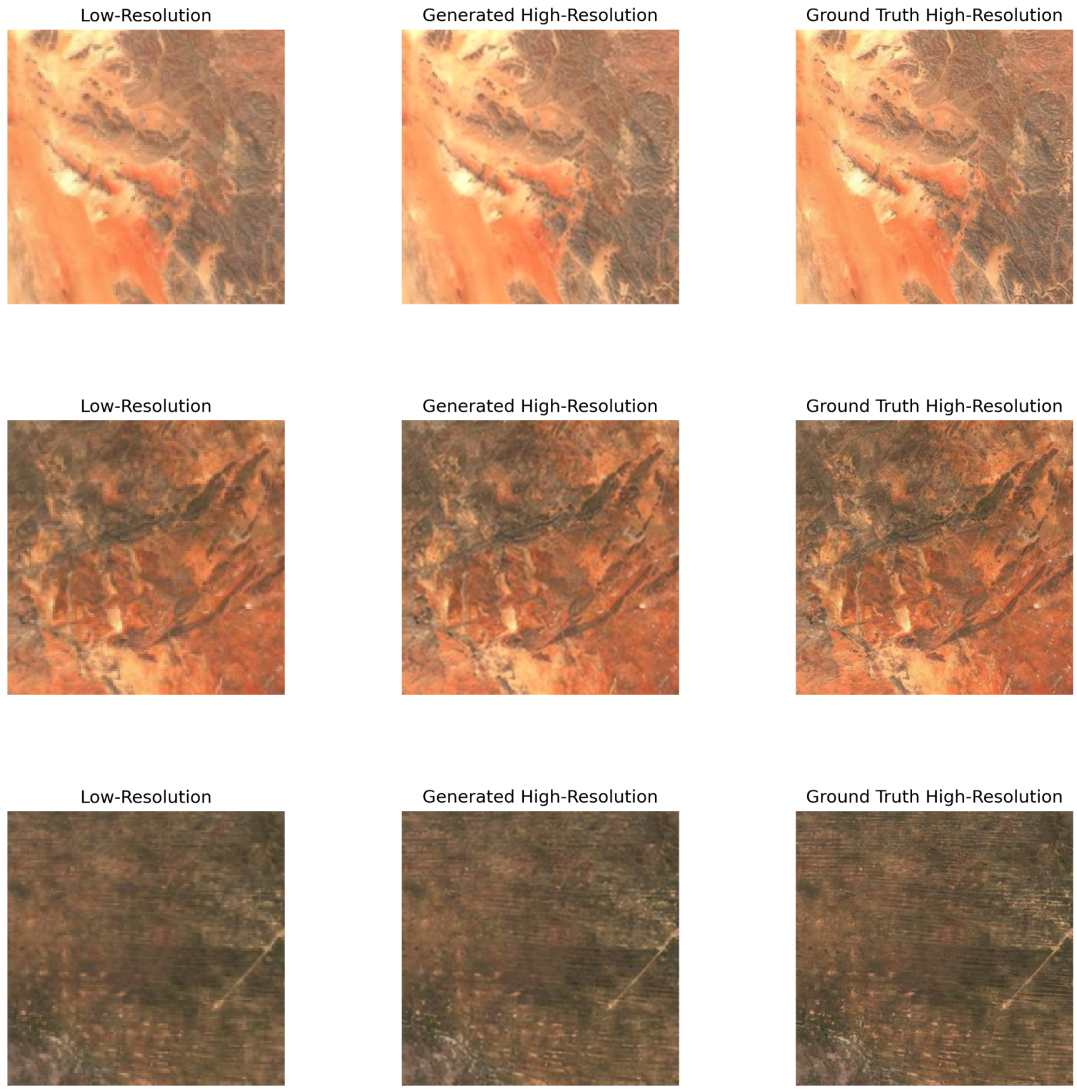
After processing my Sentinel-2 images of Namibia through ESRGAN, I evaluated the performance using standard image super-resolution metrics: Structural Similarity Index Measure (SSIM) and Peak Signal-to-Noise Ratio (PSNR). SSIM, a score ranging from -1 (complete dissimilarity) and 1(perfect similarity), measures similarity between the ground truth high-resolution image and the ESRGAN generated image. PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise affecting it. Over 3 images, the images achieved an average PSNR of 30.20 dB and SSIM of 0.7521. These results show a significant improvement in image quality when compared to the original low-resolution image. Below is an example of these results.



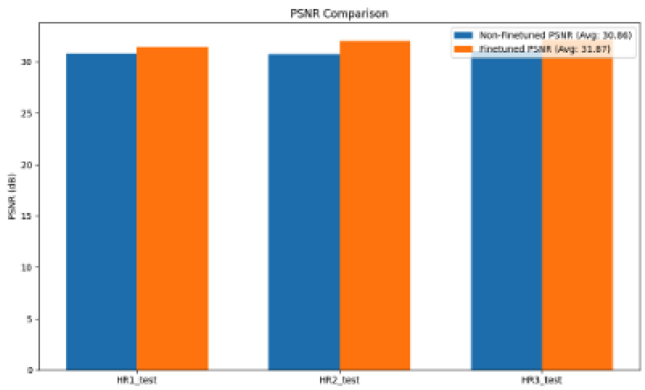
After realizing the initial success, I continued by finetuning ESRGAN with data from my Namibia dataset. In doing this, I aimed to extract more nuanced features specific to the Namibian landscape. The finetuning data consisted of 22 low-resolution images and their corresponding 22 high-resolution counterparts. Training lasted 60 epochs and filtered over multiple learning rates to optimize model parameters.

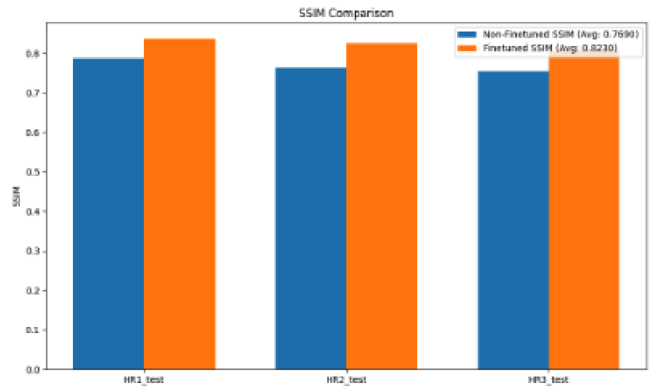


Following training, I tested the finetuned ESRGAN on the same three test images used in the ESRGAN in order to have comparable results. The metrics showed improved results with an average PSNR of 31.14 dB and an average SSIM of 0.8061. The results are visualized in the figure below.

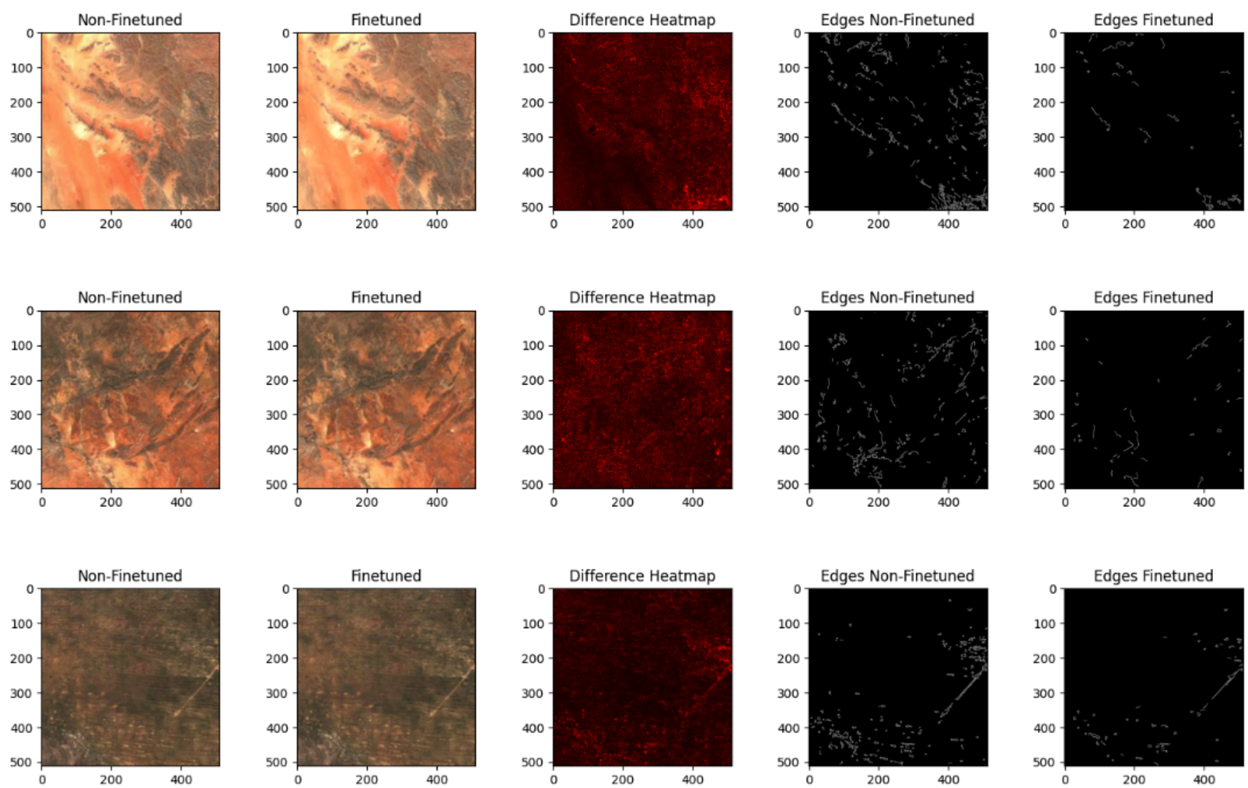


A comparison of the non-finetuned and finetuned ESRGAN shows significant improvements. The finetuning process increased PSNR by 3.03% and SSIM by 11.79%.





Visually comparing the pre-finetuned and finetuned ESRGAN generated images reveals some interesting information. Notably, the edges, created by a simple sobel filter, seem to be significantly more prominent in the non-finetuned images. This alludes to the fact that although the finetuned model has favorable SSIM and PSNR metrics it could reduce the sharpness of certain features that might be important in downstream ML tasks related to mining.



In the future, I would look to improve results by expanding the dataset of satellite imagery of Namibia, and use various bands from Sentinel-2, like R60 and R10. Along with that, the optimization of finetuning ESRGAN, in terms of data and hyperparamters, can be further explored.

This project details the importance of modern technology in advancing the mining industry, particularly the role of satellite imagery in locating natural resource deposits. By successfully implementing and finetuning ESRGAN, I demonstrated the possibility for significant super-resolution on low-resolution satellite imagery. Additionally, while the training of StyleGAN3 did not yield immediate results, the model's ability for perturbing latent spaces presents a promising avenue. This project highlights the potential of super-resolution within the mining sector and exemplifies the feasibility of improving image quality to support in resource identification and analysis.

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