Evaluating Performance Boost in Base Masked Autoencoders by Enhancing Data Augmentation with Generative Models

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ABSTRACT

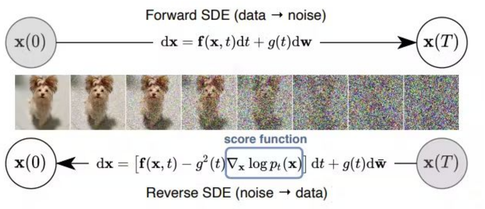
This project investigates the potential of data augmentation using generative models to improve the performance of Masked Autoencoders (MAEs) in unsupervised learning tasks. MAEs reconstruct masked portions of images, learning efficient representations without labeled data. The study compares four configurations: a baseline MAE trained on 200 RGB images from the KAIST Multispectral Pedestrian Dataset, an enhanced MAE trained on the same dataset augmented with 200 synthetic images generated by a Denoising Diffusion Probabilistic Model (DDPM) and a baseline MAE trained on 200 thermal images from the KAIST Multispectral Pedestrian Dataset, an enhanced MAE trained on the same dataset augmented with 200 synthetic images generated by CycleGAN. Results show 45% increased loss when data augmentation is used with diffusion models but a 9% decrease in training loss when CycleGAN's are employed.

INTRODUCTION

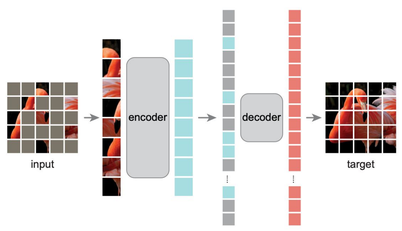
Masked Autoencoders (MAEs) are a powerful tool for unsupervised learning, particularly in scenarios where labeled data is limited. By reconstructing randomly masked patches of input images, MAEs can learn robust representations of image features. However, their performance is often constrained by the diversity and quantity of available training data. This project explores whether introducing synthetic images generated by diffusion models can mitigate this limitation. Diffusion models, known for their ability to create high-quality and diverse synthetic data, were used to augment the training dataset. By comparing the performance of MAEs trained on original and augmented datasets, this study aims to establish a scalable methodology for improving model robustness and generalization.

BACKGROUND INFORMATION

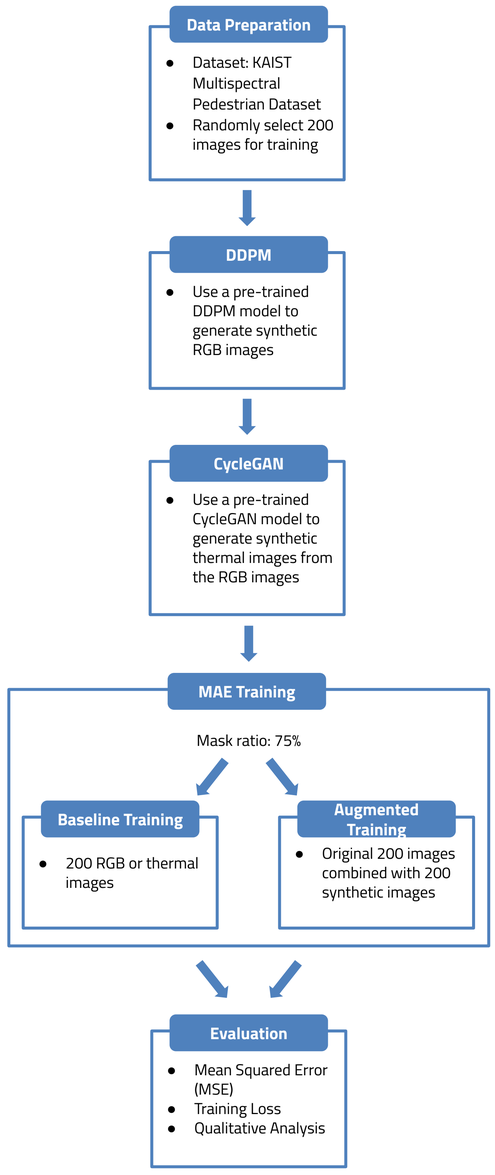
What Is Denoising Diffusion Probabilistic Model (DDPM)?



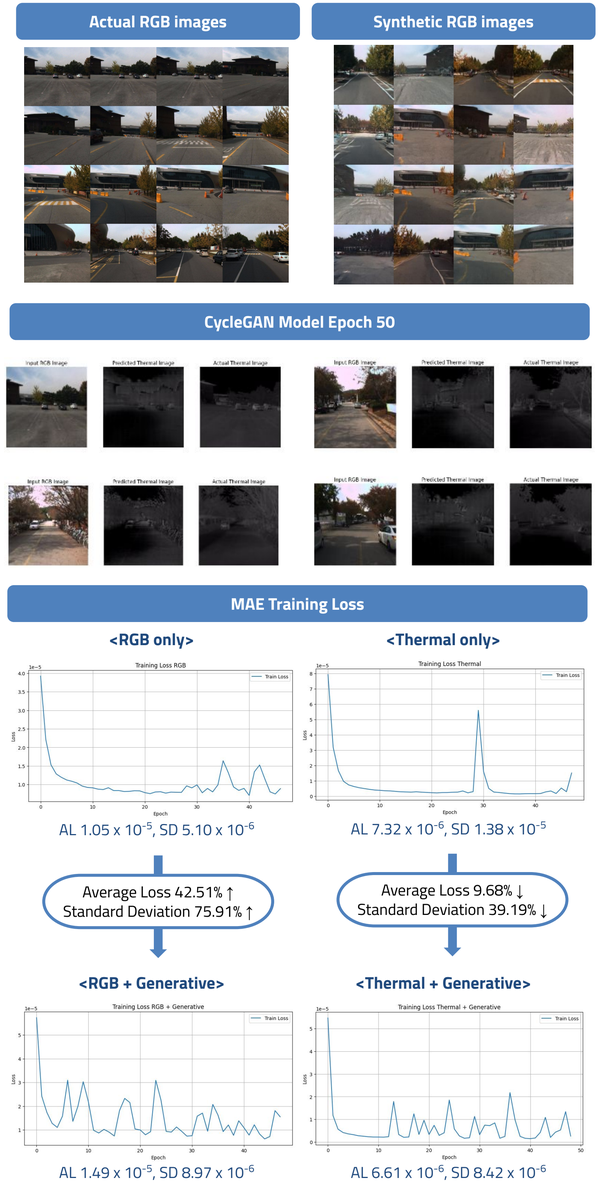
What Is Masked Autoencoders (MAE)?



METHODOLOGY



RESULTS



CONCLUSION

This study aimed to evaluate the impact of generative data augmentation on Masked Autoencoders (MAEs) by incorporating synthetic RGB and thermal images generated by DDPM and CycleGAN models.

The results indicate mixed outcomes: while the inclusion of synthetic images improved the performance of the thermal dataset, it increased the loss and variability in the RGB dataset. These results suggest that the impact of generative data augmentation depends on the dataset and input modality.

- RGB Dataset: The addition of generative images likely introduced excessive complexity or noise that hindered the model's ability to learn robust features effectively.
- Thermal Dataset: Generative images enhanced performance, potentially due to the simplicity of grayscale images, which introduced less noise during training.

This study demonstrates the potential of generative data augmentation to improve MAE performance in specific conditions, particularly in low-data regimes for thermal imaging. However, the challenges observed in the RGB dataset highlight the importance of careful dataset design and the quality of synthetic data.

FUTURE DIRECTIONS

- Conduct experiments with larger datasets and varied augmentation techniques to mitigate noise and improve generalization.
- Investigate the quality and diversity of synthetic images generated by diffusion and GAN models, as these factors may significantly influence performance.
- Explore the integration of domain-specific priors or hybrid augmentation approaches to improve results across diverse input modalities.

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