Image Degredation Makes Models More Robust

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Background

- Convolutional Neural Networks (CNNs) usually trained with **images of normal quality**
- Real-life images often **imperfect**
- **Data augmentation:** Adding diversity to datasets by applying transformations (e.g., cropping or rotating images)[1]
- **ResNet-50** better on images with Gaussian blur than motion blur and Gaussian noise[2]
- No research on **over-** and **underexposure**

Research Question / Exploratory Design

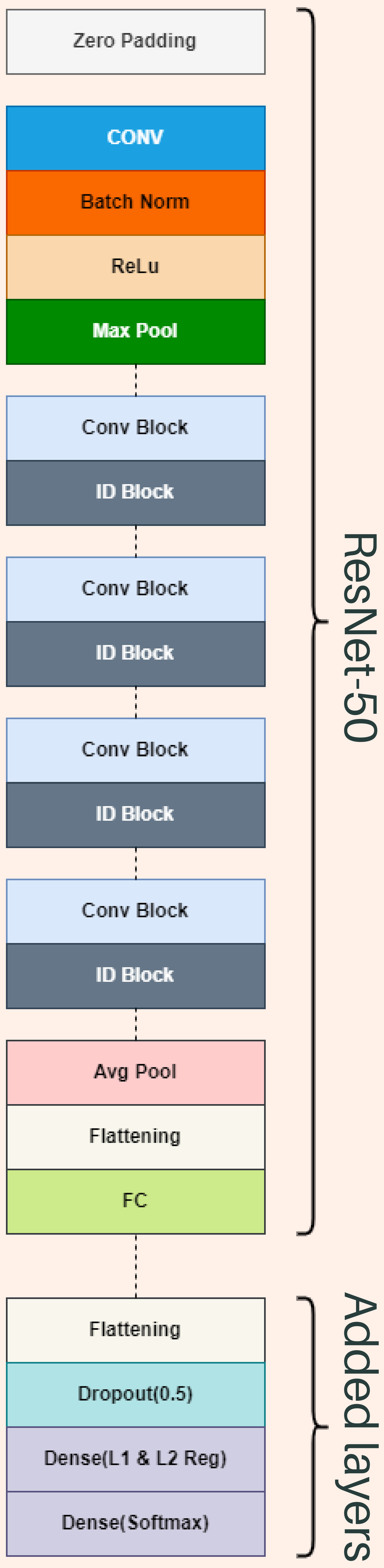
- How well can **CNNs trained on a specific type of image** (normal or some degredation) **generalize to other image types?**
- **Seven models** of identical architecture
- Same training images, **different degredations**
- **Testing on all degredation types**

Dataset

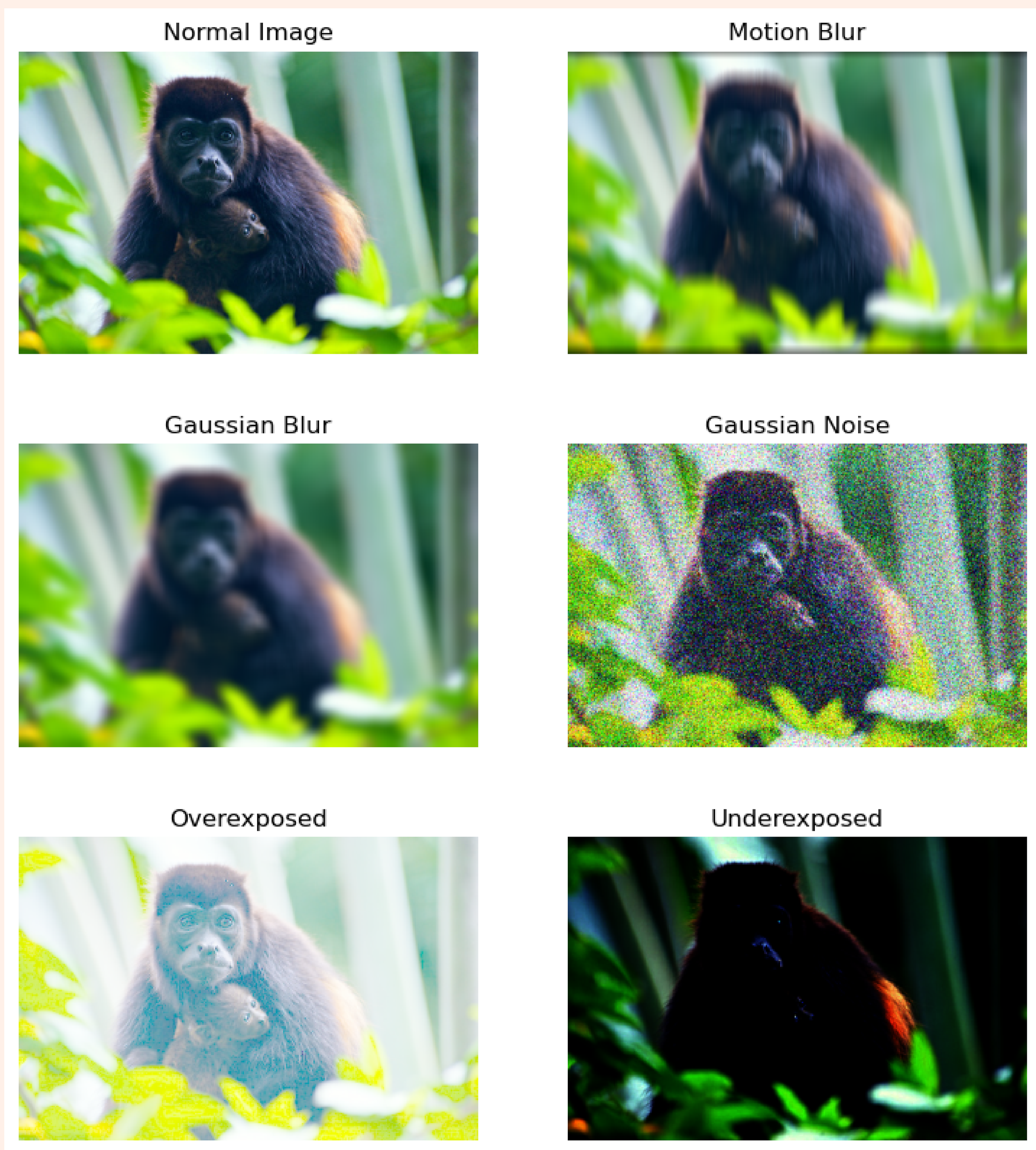
- Animal Image Classification Dataset
- 12 categories
- 17,183 images

Model Architecture / Training

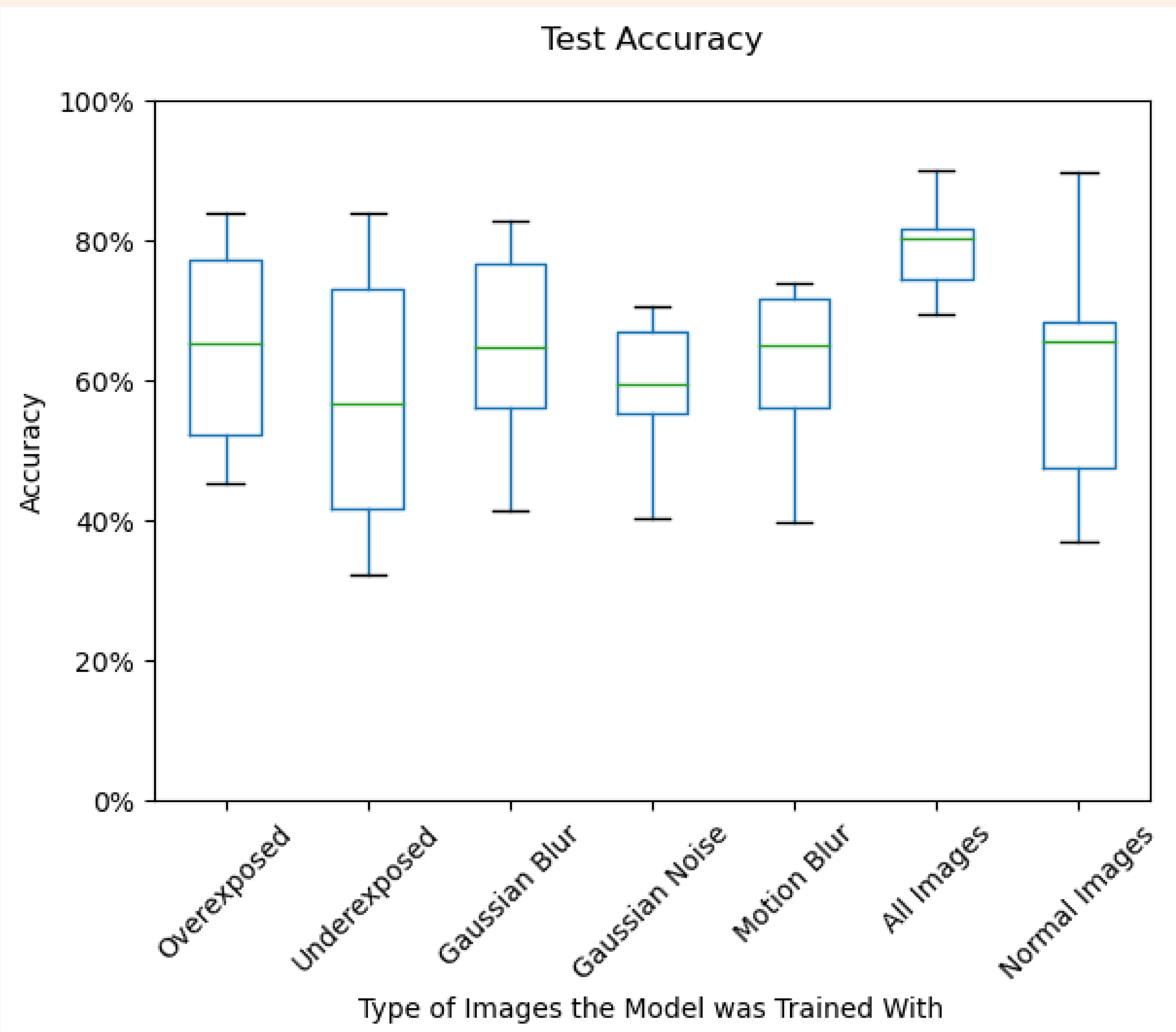
- **ResNet-50** base[3] trained on Imagenet data
- **ADAM** optimizer with **adaptive learning rate**
- **Early stopping** based on validation loss
- **Seven models** (1x normal images, 1 per augmentation, 1x mixed model)

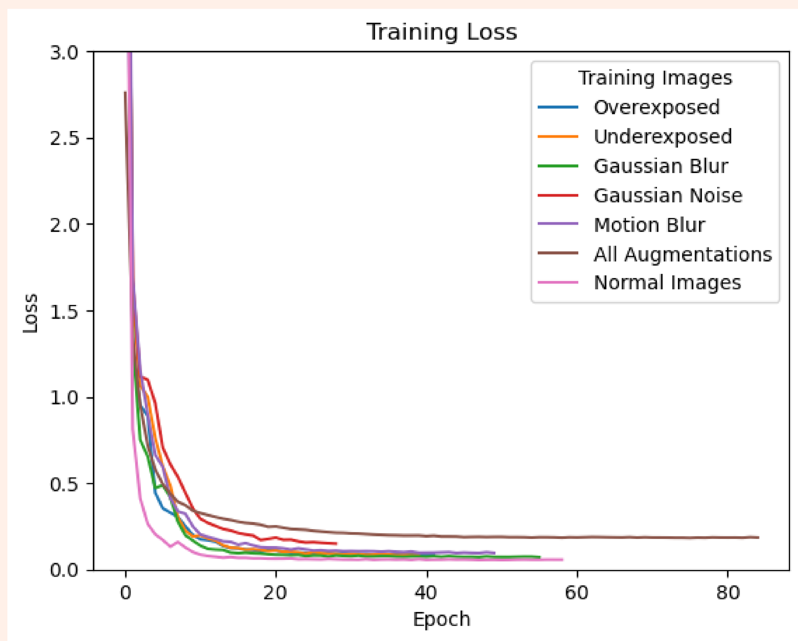


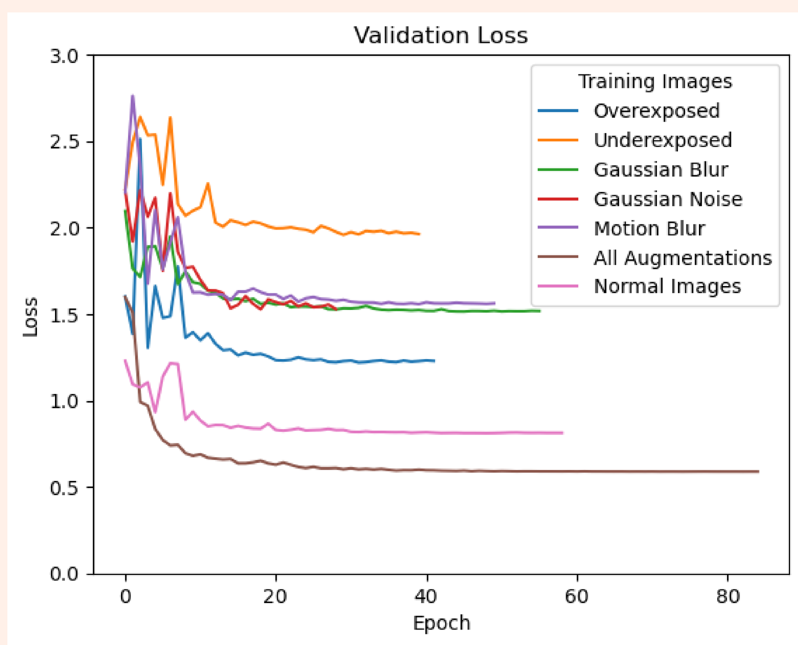
Data Augmentation



Results







Conclusion

- Trained on normal images does not generalize well to degraded images
- Trained on degraded images generalizes well to normal images
  - High-level features still learned
- Gaussian noise biggest problem
- Trained on all generalizes best

! Training data should include artificially degraded images

References:
1.) Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. Journal of big data, 6(1), 1-48.
2.) Roy, P., Ghosh, S., Bhattacharya, S., & Pal, U. (2018). Effects of degradations on deep neural network architectures. arXiv preprint arXiv:1807.10108.
3.) Koonce, B. (2021). ResNet 50. In Convolutional neural networks with swift for tensorflow (pp. 63-72). Apress, Berkeley, CA.

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