Motivation

In practical applications, images are often captured under less than ideal conditions, leading to the introduction of various types of noise. For instance, images captured in low-light environments can be affected by Gaussian noise, while rapid movement during capture can result in motion blur. Additionally, limitations in sensor quality can give rise to salt-and-pepper noise. Beyond the impact of noise, these images are frequently subjected to compression algorithms, such as JPEG or JPEG2000, to enable efficient storage and transmission. While these compression methods are widely used, they can lead to the loss of high-frequency details and introduce blocky artefacts, further degrading image quality. The combination of noise and compression artefacts can significantly influence the performance of neural networks, which are typically trained on clean, uncompressed images. Therefore, a comprehensive investigation into the effects of these real-world conditions on the performance of neural networks is essential. This will not only improve our understanding of their robustness under such conditions but also inform the development of more resilient models and better image quality metrics that consider both noise and compression artefacts.

Contribution

- Robustness Analysis under Noisy and Compressed Conditions: This project is one of the first to investigate the robustness of neural networks to different codecs under noisy conditions. This is a significant contribution as it reflects a common real-world scenario that has been largely overlooked in the literature.

- Analysis of Noise Interactions: The project will analyse the interactions between different types of noise and their combined impact on the performance of neural networks. This will provide insights into which types of noise are dominant and how they interact with each other.

- Investigation of Compression and Noise Interactions: The project will also investigate how compression interacts with different types of noise and how this affects the performance of neural networks. This could lead to the development of new compression algorithms that are more robust to specific types of noise.

- Geometrical Analysis of Noise Impact: The project will provide a geometrical analysis of the impact of different types of noise on the performance of neural networks. This will offer a more detailed understanding of how noise affects these models and could lead to the development of more robust architectures.

- Novel Deep Learning-based Compression Algorithm: The project will propose a novel deep learning-based compression algorithm specifically designed for noisy inputs. This is a significant advancement over traditional compression algorithms that do not take into account the specific characteristics of the input.
- Fine-tuning Based on Dominant Noise: The project will introduce a novel approach of fine-tuning the proposed neural compression network based on the dominant noise

identified from the noise interaction analysis. This could lead to models that are more robust to specific types of noise, increasing overall robustness.

Experiments Plan

Experiment 1: Baseline Image Classification

- Dataset: Subset of Caltech101
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy

This experiment serves as the baseline for the project. It helps to establish the performance of the DL model on the ImageNet dataset without any noise or compression. This will provide a reference point for the subsequent experiments.

Experiment 2: Image Classification with Different Compression Techniques

- Dataset: Subset of Caltech101
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification with compression (JPEG and JPEG2000)
- Evaluation Metrics: Top 1 and Top 5 validation accuracy, Bit-per-Pixel, Average Shift Distance, etc.

This experiment is designed to evaluate the impact of different compression techniques on the performance of the ResNet80 model. Specifically, we will use JPEG, a widely used compression standard in many applications and platforms such as IoT surveillance cameras, and JPEG2000, a newer version offering higher efficiency. The results of this experiment will help identify which compression techniques are most compatible with the model and which ones degrade its performance the most.

Experiment 3a: Image Classification with Traditional Noise

- Dataset: Subset of Caltech101 (with selected traditional noise: Gaussian Noise, Motion Blur and Salt and Pepper Noise)
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy , Average Shift Distance, etc.

In this experiment, we aim to assess the performance of the DL model under the influence of traditional types of noise that are commonly encountered in real-world scenarios. Gaussian Noise, often introduced by electronic transmission, represents the random variation of brightness or colour information in images. Motion Blur is a frequent artefact in images captured by moving cameras or of moving objects, typical in surveillance or vehicle-mounted cameras. Salt and Pepper Noise, characterised by sparsely occurring white and black pixels, can be caused by sudden disruptions during image transmission or processing. Understanding the model's robustness to these traditional types of noise can provide insights into its performance in practical applications.

Experiment 3b: Image Classification with New Trend Noise

- Dataset: Subset of Caltech101 (with selected new trend noise: Colour Variation and Brightness)
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy, Average Shift Distance, etc.
-

This experiment is designed to evaluate the performance of the ResNet80 model under the influence of newer types of noise that are increasingly relevant in today's diverse imaging conditions. Colour Variation is a common issue in images captured under different lighting conditions or with different imaging devices, which is typical in the era of ubiquitous imaging devices ranging from professional cameras to mobile phones. Brightness variation, another common issue, can occur due to changes in lighting conditions or the camera's auto-exposure settings, which is a frequent scenario in outdoor imaging or varying indoor lighting conditions. Understanding the model's robustness to these new trend types of noise can provide insights into its performance in contemporary real-world applications.

Experiment 4: Image Classification with Compression on Noisy Images

- Dataset: Subset of Caltech101 (with selected traditional and new trend noise, compressed with JPEG and JPEG2000)
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy, Average Shift Distance, etc.

This experiment is designed to simulate a common real-world scenario where images are both noisy and compressed. In many practical applications, such as surveillance cameras operating in various weather conditions or mobile phone cameras used in diverse lighting conditions, images are captured in less than ideal conditions, leading to noise. Then, for efficient storage or transmission, these images are often compressed. By applying both traditional and new trend noise to the images and then compressing them using JPEG and JPEG2000, we can evaluate the performance of the ResNet80 model under these combined conditions. This can provide valuable insights into the model's robustness when dealing with real-world images that are both noisy and compressed.

Experiment 5a: Image Classification with Combined Noise

- Dataset: ImageNet (with all combinations of traditional and new trend noise: Gaussian noise with Colour Variation, Gaussian noise with Brightness, Motion blur with Colour Variation, Motion blur with Brightness)
- Model: VGG16, VGG19, ResNet50, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy, Average Shift Distance, etc.

This experiment is designed to simulate more complex real-world scenarios where images are affected by multiple types of noise simultaneously. For instance, an image captured by a surveillance camera at night (leading to Gaussian noise due to low light) might also be affected by varying lighting conditions (leading to colour variation). Similarly, an image captured by a mobile phone camera in motion (leading to motion blur) might also be affected by changes in the brightness of the scene. By applying all combinations of traditional and new trend noise to the images, we can evaluate the performance of the ResNet80 model under these combined conditions. This can provide valuable insights into the model's robustness when dealing with real-world images that are affected by multiple types of noise. Furthermore, this experiment will allow us to identify the dominant noise in these combinations and understand how different types of noise interact with each other.

Experiment 5b: Image Classification with Compressed Combined Noise

- Dataset: Subset of Caltech101 (with all combinations of traditional and new trend noise: Gaussian noise with Colour Variation, Gaussian noise with Brightness, Motion blur with Colour Variation, Motion blur with Brightness, and Compressed)
- Model: VGG16, MobileNet, DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy, Average Shift Distance, etc

Building on the previous experiment, this experiment introduces an additional layer of complexity by compressing the noisy images. In real-world scenarios, images are not only affected by noise but are also often compressed for efficient storage and transmission. By compressing the noisy images using widely used codecs (JPEG and JPEG2000), we aim to simulate these conditions and evaluate the performance of the ResNet80 model. This will allow us to understand how compression interacts with other types of noise and whether the compression noise dominates or exacerbates the impact of other types of noise on the model's performance.

Experiment 6: Fine-tuning the NN with Traditional Codec Based on Dominant Noise and Applying to Other Noises

- Dataset: Subset of Caltech101 (with dominant noise identified from Experiment 6, and other noises)
- Model: VGG16, MobileNet (FineTuned), DenseNet
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy

This experiment aims to explore the potential benefits of fine-tuning the ResNet80 model based on the dominant noise identified from the previous experiments. In real-world scenarios, certain types of noise may be more prevalent or impactful than others. By fine-tuning the model to be more robust to this dominant noise, we hope to improve its overall performance. However, it's also important that the model remains robust to other types of noise. Therefore, after fine-tuning the model on the dominant noise, we will also evaluate its performance on images affected by other common types of noise. This will provide insights into the trade-offs involved in fine-tuning the model for specific types of noise.

Experiment 7: Propose and Fine-tune the Novel Machine Learning Compression Algorithm on Dominant Noise and Applying to Other Noises

- Dataset: Subset of Caltech101 (with combined traditional and new trend noise)
- Model: MobileNet (with a novel machine learning compression algorithm)
- Task: Image Classification
- Evaluation Metrics: Top 1 and Top 5 validation accuracy

In this experiment, we propose an initial idea for a novel attention-based neural compression network that is specifically designed to handle noisy inputs. The proposed architecture includes a noise-aware attention module in both the encoder and decoder, which modulates the feature maps based on the estimated noise level in the image. This ensures that the network focuses more on the less noisy regions of the image during both compression and decompression. The network also includes an adaptive bottleneck layer, whose size changes based on the estimated noise level, allowing the network to adjust its compression rate based on the quality of the input image. Finally, we propose a noise-adaptive loss function that balances between reconstruction accuracy and noise suppression, with more emphasis on noise suppression for noisier inputs. We aim to fine-tune this novel network on the dominant noise identified from the previous experiments, and evaluate its performance on images affected by other common types of noise. This experiment will provide preliminary insights into the potential benefits of using machine learning-based compression for noisy images, and the effectiveness of the proposed noise-aware attention mechanism and adaptive bottleneck layer. (initial general idea)

Reference

[1] Lukin, Vladimir, et al. "Compression of Noisy Images Taking into Account Visual Quality: A Comprehensive Study." *Research Developments in Science and Technology Vol. 8*(2022): 89-109.
[2] Al-Shaykh, Osama K., and Russell M. Mersereau. "Lossy compression of noisy images." *IEEE Transactions on Image Processing* 7.12 (1998): 1641-1652.
[3] Ponomarenko, Nikolay, et al. "Lossy compression of images with additive noise." *Advanced Concepts for Intelligent Vision Systems: 7th International Conference, ACIVS 2005, Antwerp, Belgium, September 20-23, 2005. Proceedings 7*. Springer Berlin Heidelberg, 2005.
[4] Ponomarenko, Nikolay, et al. "Estimation of accessible quality in noisy image compression." *2006 14th European Signal Processing Conference*. IEEE, 2006.
[5] Chan, Tommy CL, Tai-Chiu Hsung, and DP-K. Lun. "Improved MPEG-4 still texture image coding under noisy environment." *IEEE transactions on image processing* 12.5 (2003): 500-508.
[6] Ponomarenko, Nikolay, et al. "Lossy compression of images with additive noise." *Advanced Concepts for Intelligent Vision Systems: 7th International Conference, ACIVS 2005, Antwerp, Belgium, September 20-23, 2005. Proceedings 7*. Springer Berlin Heidelberg, 2005.
[7] Ponomarenko, Nikolay, et al. "Lossy compression of noisy images based on visual quality: a comprehensive study." *EURASIP Journal on Advances in Signal Processing* 2010 (2010): 1-13.
[8] Theis, Lucas, et al. "Lossy compression with gaussian diffusion." *arXiv preprint arXiv:2206.08889* (2022).
[9] Cheng, Ka Leong, Yueqi Xie, and Qifeng Chen. "Optimizing image compression via joint learning with denoising." *European Conference on Computer Vision*. Cham: Springer Nature Switzerland, 2022.
[10] Lukin, Vladimir, et al. "Lossy compression of multichannel remote sensing images with quality control." *Remote Sensing*12.22 (2020): 3840.
[11] Yee, David, et al. "Medical image compression based on region of interest using better portable graphics (BPG)." *2017 IEEE international conference on systems, man, and cybernetics (SMC)*. IEEE, 2017.
[12] Odegard, Jan E., et al. "Joint compression and speckle reduction of SAR images using embedded zerotree models." *Workshop on Image and Multidimensional Digital Signal Processing*. 1996.
[13] Starck, J-L., F. Murtagh, and M. Louys. "High quality astronomical image compression." *Vistas in Astronomy* 41.3 (1997): 439-445.
[14] White, Richard L., and Jeffrey W. Percival. "Compression and progressive transmission of astronomical images." *Advanced Technology Optical Telescopes V*. Vol. 2199. SPIE, 1994.
[15] Chang, S. Grace, Bin Yu, and Martin Vetterli. "Adaptive wavelet thresholding for image denoising and compression." *IEEE transactions on image processing* 9.9 (2000): 1532-1546.
[16] Piau, Rémi, Thomas Maugey, and Aline Roumy. "Learning on entropy coded images with cnn." *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023.
[17] Harell, Alon, Yalda Foroutan, and Ivan V. Bajic. "VVC+ M: Plug and Play Scalable Image Coding for Humans and Machines." *arXiv preprint arXiv:2305.10453* (2023).
[18] de Andrade, Anderson, et al. "Conditional and Residual Methods in Scalable Coding for Humans and Machines." *arXiv preprint arXiv:2305.02562* (2023).
[19] Fischer, Kristian, et al. "Saliency-Driven Hierarchical Learned Image Coding for Machines." *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023.
[20] Fischer, Kristian, et al. "Analysis of neural image compression networks for Machine-To-Machine communication." *2021 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2021.
[21] Choi, Hyomin, and Ivan V. Bajić. "Scalable image coding for humans and machines." *IEEE Transactions on Image Processing* 31 (2022): 2739-2754.
[22] Duan, Lingyu, et al. "Video coding for machines: A paradigm of collaborative compression and intelligent analytics." *IEEE Transactions on Image Processing* 29 (2020): 8680-8695.
[23] Liu, Tie, et al. "Learnt Mutual Feature Compression for Machine Vision." *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2023.
[24] Yang, En-Hui, Hossam Amer, and Yanbing Jiang. "Compression helps deep learning in image classification." *Entropy* 23.7 (2021): 881.

[25] Marie, Alban, et al. "Video Coding for Machines: Large-Scale Evaluation of Deep Neural Networks Robustness to Compression Artifacts for Semantic Segmentation." *2022 IEEE 24th International Workshop on Multimedia Signal Processing (MMSP)*. IEEE, 2022.
[26] Marie, Alban, et al. "Expert training: Enhancing ai resilience to image coding artifacts." *Electronic Imaging, Image Processing: Algorithms and Systems XX*. 2022.
[27] Hendrycks, Dan, and Thomas Dietterich. "Benchmarking neural network robustness to common corruptions and perturbations." *arXiv preprint arXiv:1903.12261* (2019).
[28] Hendrycks, Dan, and Thomas G. Dietterich. "Benchmarking neural network robustness to common corruptions and surface variations." *arXiv preprint arXiv:1807.01697* (2018).
[29] Dodge, Samuel, and Lina Karam. "A study and comparison of human and deep learning recognition performance under visual distortions." *2017 26th international conference on computer communication and networks (ICCCN)*. IEEE, 2017.
[30] Geirhos, Robert, et al. "Comparing deep neural networks against humans: object recognition when the signal gets weaker." *arXiv preprint arXiv:1706.06969* (2017).
[31] Temel, Dogancan, et al. "CURE-TSR: Challenging unreal and real environments for traffic sign recognition." *arXiv preprint arXiv:1712.02463* (2017).
[32] Dogancan Temel, Jinsol Lee, and Ghassan AlRegib. Cure-or: Challenging unreal and real environ- ments for object recognition. *ICMLA*, 2018.
[33] Dodge, Samuel, and Lina Karam. "Quality resilient deep neural networks." *arXiv preprint arXiv:1703.08119* (2017).
[34] Dodge, Samuel F., and Lina J. Karam. "Quality robust mixtures of deep neural networks." *IEEE Transactions on Image Processing* 27.11 (2018): 5553-5562.
[35] Hossain, Md Tahmid, et al. "Distortion robust image classification using deep convolutional neural network with discrete cosine transform." *2019 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2019.
[36] Hu, Chengyin, et al. "Impact of Light and Shadow on Robustness of Deep Neural Networks." *arXiv preprint arXiv:2305.14165* (2023).
[37] Hu, Chengyin, and Weiwen Shi. "Impact of Colour Variation on Robustness of Deep Neural Networks." *arXiv preprint arXiv:2209.02832* (2022).
[38] Hu, Chengyin, and Weiwen Shi. "Impact of Scaled Image on Robustness of Deep Neural Networks." *arXiv preprint arXiv:2209.02132* (2022).
[39] De, Kanjar, and Marius Pedersen. "Impact of colour on robustness of deep neural networks." *Proceedings of the IEEE/CVF international conference on computer vision*. 2021.
[40] Carrasco, Javier, et al. "Laconic Image Classification: Human Vs. Machine Performance". Proceedings of the 29th ACM International Conference on Information &Amp; Knowledge Management, 2020.
[41] Le, Nam, et al. "Bridging the Gap Between Image Coding for Machines and Humans." *2022 IEEE International Conference on Image Processing (ICIP)*. IEEE, 2022.
[42] Lukin, Vladimir, et al. "Lossy Compression of Remote Sensing and Dental Images Corrupted by Spatially Correlated Noise." *Conference on Integrated Computer Technologies in Mechanical Engineering–Synergetic Engineering*. Cham: Springer International Publishing, 2021.
[43] Naumenko, Victoria, Vladimir Lukin, and Sergey Krivenko. "Analysis of Noisy Image Lossy Compression by BPG." *Conference on Integrated Computer Technologies in Mechanical Engineering–Synergetic Engineering*. Cham: Springer International Publishing, 2021.
[44] Kovalenko, Bogdan, et al. "Analysis of noisy image lossy compression by BPG using visual quality metrics." *2021 IEEE 3rd International Conference on Advanced Trends in Information Theory (ATIT)*. IEEE, 2021.
[45] Dodge, Samuel, and Lina Karam. "A study and comparison of human and deep learning recognition performance under visual distortions." *2017 26th international conference on computer communication and networks (ICCCN)*. IEEE, 2017.