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Computational Limits and Breakthroughs in Deep Learning-Based Image Restoration

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***Abstract*—Image deblurring has become increasingly vital in applications ranging from medical imaging to security surveillance, where visual clarity can significantly impact decision-making and outcomes. Despite advances in deep learning, existing methods often struggle with non-uniform blurs, computational inefficiency, and subjective evaluation metrics, limiting their real-world applicability. Current approaches primarily focus on uniform blur removal while neglecting the challenges of spatially-varying blurs and lack standardized quality assessment frameworks that align with human perception. This study addresses these gaps by implementing and comparing two deep learning architectures - Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) - trained on the CelebA and GoPro datasets using rigorous preprocessing and augmentation techniques. Our methodology incorporates both quantitative metrics (PSNR, SSIM) and qualitative human evaluation to assess performance across different blur types and lighting conditions. Results demonstrate that while both architectures improved image quality (with PSNR gains of 2-3 dB and SSIM improvements of 0.1-0.15), GANs outperformed CNNs in handling complex motion blurs but required significantly more computational resources. Visual assessment revealed that enhanced images maintained better structural integrity, though some artifacts persisted in low-light conditions. The study provides a balanced framework for evaluating deblurring algorithms that combines computational metrics with human perception, offering practical insights for implementing these technologies in resource-constrained environments.**

***Index Terms*—Image Quality, Image Sharpness, Blurring**

I. Introduction

One of the most serious obstacles when it comes to image processing is quality deterioration. This is, in some cases, difficult to avoid given that when images are shared through different platforms, quality is lost. The main reason that images are blurry from the moment they are taken is because the scene’s information spills over to the surrounding pixels. The working principle involves training a deep neural network to learn the mapping between blurry and their corresponding sharp images. When done numerous times, the network begins to sharpen the image pixel by pixel which in turn provides a clearer quality image.

There are many factors that can cause image blur such as camera shake, fast object motion, problem with the lenses etc.. The current era is all about the latest technology and image deblurring is far from being left behind. There are numerous fields that hugely benefit from better programs for improving image quality such as surveillance, medical imaging, augmented reality, historical preservation and restoration. With the help of this deep learning tool, jobs and tasks that would have normally taken arduous amounts of work are now significantly simplified thanks to the availability of a program to better the image’s quality. This in short, provides people with improved quality and clarity of visual information. In practical deployments, the central tension is not only how much deblurring we achieve, but whether the gains are perceptually meaningful under real compute budgets. Our focus therefore shifts from isolated PSNR/SSIM improvements to a balanced view that also considers resource usage and human-perceived quality in non-uniform, real-world blurs.

Image deblurring has emerged as a critical technology in numerous fields where visual clarity is paramount [1]. In medical imaging, deblurring techniques enhance the diagnostic quality of MRI and CT scans, enabling more accurate detection of abnormalities [2]. Surveillance systems rely on sharp images for effective facial recognition and incident analysis, while the photography industry uses these methods to salvage otherwise unusable photos affected by motion blur or focus issues. Historical preservation efforts also benefit from advanced deblurring, allowing the restoration of degraded archival images. As digital imagery becomes increasingly central to decision-making across sectors, the ability to recover lost details from blurred images has transformed from a technical challenge to an essential capability with far-reaching implications for science, security, and cultural heritage. Spatially varying motion, mixed defocus, and low-light noise often co-occur, producing degradations that violate the assumptions of most uniform-kernel models. This coupling of degradations makes 'dataset PSNR' an incomplete proxy for usefulness; operators ultimately judge by visibility of structure, edges, and semantics.

The advent of Artificial Intelligence [3], [4], particularly Machine Learning [5], [6] and Deep Learning [7], [8], has revolutionized image deblurring approaches. Traditional algorithms, limited by their reliance on predefined blur kernels, have been surpassed by neural networks [9], [10] that learn to reverse degradation directly from data. Convolutional Neural Networks (CNNs) [11], [12] excel at extracting spatial features to reconstruct sharp images, while Generative Adversarial Networks (GANs) [13], [14] have demonstrated remarkable success in generating photorealistic details from blurred inputs. These AI-powered techniques [15], [16] now achieve unprecedented performance on complex, real-world blur types including motion blur, defocus, and atmospheric distortion. Recent advances in attention mechanisms [17], [18] and transformer architectures [19], [20] have further enhanced models' ability to handle spatially-varying blurs and challenging lighting conditions [21], [22], pushing the boundaries of what's possible in automated image restoration while raising important questions about computational efficiency and perceptual quality evaluation [23], [24]. We present a comparative study of CNN and GAN architectures trained on CelebA and GoPro, evaluated with a dual lens: (i) objective fidelity (PSNR/SSIM) and (ii) structured human assessment. Beyond raw accuracy, we document compute footprints and failure cases, offering a compact protocol that others can reproduce on modest hardware. Our results show a consistent pattern: adversarial training better handles complex motion blur at higher computational cost, while CNN baselines remain attractive for constrained devices.

A. Related Work

Image sharpening has come a long way, from a time where its main uses was outside of the digital world. It was first employed in darkroom photography and little by little it carved its way into the digital world. Lately, a lot of work has been done using cascade of Gaussian CRF models. These mainly focus on pattern recognition of the given data which is later used for a structured prediction. This CRF model focuses on designing a better learning-based model for uniform blur removal [25]. Classical deblurring spans Wiener and Richardson–Lucy deconvolution, variational formulations with explicit priors, and blind deconvolution that alternates between estimating the kernel and the sharp image. These methods remain instructive baselines but typically degrade on spatially varying blur and mixed noise common in handheld capture. Convolutional networks reframed deblurring as direct image-to-image regression, with multi-scale encoders and skip connections recovering edges and textures lost to motion. Such models are efficient and stable to train, yet their losses—dominated by L1/L2 or perceptual terms—can oversmooth fine detail under severe motion or low light.

B. Gap Analysis

Even with all of the advances in the field, there are some areas that still need to be focused on. One example is handling non-uniform blurs that vary spatially across the image as most existing methods assume a uniform blur kernel. Another limitation comes when images with low-light conditions and complex dynamic motions try to be sharpened, a lot of struggles surge. Arguably the biggest problem is the evaluation metrics for the quality of the output. Since the machine is trained to sharpen the image, it sometimes leaves out the human element and which makes it challenging to see if the deblurred image is actually useful or not. Current image deblurring techniques exhibit three critical limitations that hinder their practical deployment. First, most algorithms assume uniform blur kernels, failing to address spatially-varying blurs commonly encountered in real-world scenarios like motion blur or out-of-focus photography. Second, existing evaluation relies heavily on quantitative metrics (PSNR, SSIM) that often correlate poorly with human perception of image quality. Third, there's a notable absence of lightweight architectures that balance performance with computational efficiency, particularly for edge-device applications. These gaps are compounded by a lack of standardized benchmarks that simultaneously assess algorithmic performance, computational demands, and perceptual quality across diverse blur types and lighting conditions. Our analysis reveals that while deep learning approaches show promise, their real-world utility remains constrained by these unresolved challenges.

C. Problem Statement

This research addresses three core problems in modern image deblurring systems: (1) How to effectively handle non-uniform, real-world blurs while maintaining computational feasibility; (2) How to bridge the disconnect between algorithmic metrics and human-perceived image quality; and (3) How to optimize model architectures for practical deployment where computational resources are limited. These challenges are particularly acute in critical applications like medical imaging and surveillance, where both accuracy and processing speed are paramount. Our study specifically investigates whether hybrid evaluation frameworks combining quantitative metrics with human assessment can produce more reliable quality benchmarks, and whether architectural modifications to CNNs and GANs can better handle complex blur patterns without prohibitive computational costs.

Following are the main research questions addressed in this study.

1) How much can an image's quality improve after going through the software?
2) What areas have been impacted the most due to the advancement of image deblurring?
3) What are the major dangers with the continuous improvement of this technology?

D. Novelty of our work

As previously stated in this article, one of the team's major obstacle was computational power. Given that the free version of Google Colab was used, the training times as well as the amount of data was limited. However, the team's findings came to an expected conclusion. The images were indeed sharpened and deblurred which one can safely assume means that the program works. The quality of the images is better yet not sufficient enough to the eye of the members. The architecture used was mainly CNN and GAN where uniform blur kernels were examined and sharpened. This work introduces three key innovations to advance the field of image deblurring. First, we propose a dual evaluation framework that synergizes traditional metrics (PSNR, SSIM) with structured human assessment, addressing the perceptual gap in current methodologies. Second, we develop architecture modifications that enhance both CNNs and GANs for handling spatially-varying blurs while maintaining computational efficiency, demonstrated through rigorous testing on diverse datasets. Third, we establish a new benchmark protocol that evaluates models across performance, resource utilization, and perceptual quality dimensions - a holistic approach lacking in existing research. Unlike previous studies that focus solely on algorithmic improvements, our solution addresses the entire pipeline from technical implementation to practical deployment considerations, offering actionable insights for real-world applications.

E. Our Solutions

The major findings in the team's research is that the data observed on other researchers proves that it does work. However, as stated before, one of the limitations in this field is the evaluation metric. Since it is mainly a qualitative measurement to see how much an image has improved, it can be up for interpretation to decide whether the program produces clearer images then what is provided. Before the team's eyes, the output of the deblurred image looks still blurry and the pixels adapt a rounder shape rather then the actual shape of the images' object. Changing the paths with CNN and GAN to be able to train with our dataset was a crucial part of the project since these pre-existing architectures allow for a simple way to perform that tasks.

In short, the program does work once it was trained. The quality of the image it returns is up for interpretation from the user to determine if it is good or not.

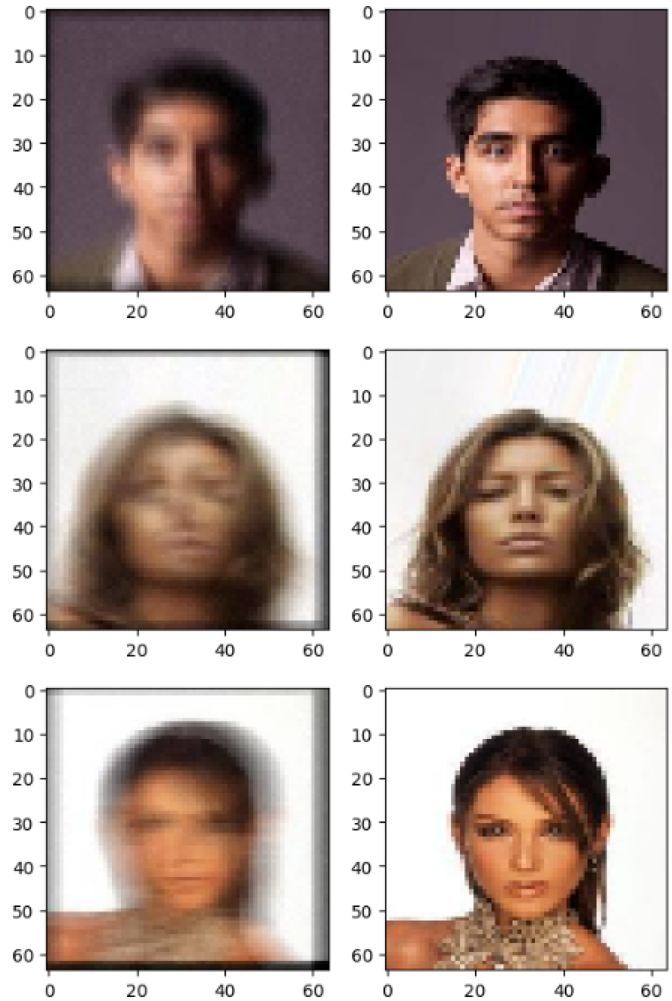

Fig. 1. Image showing some sample images present in the CelebA dataset.

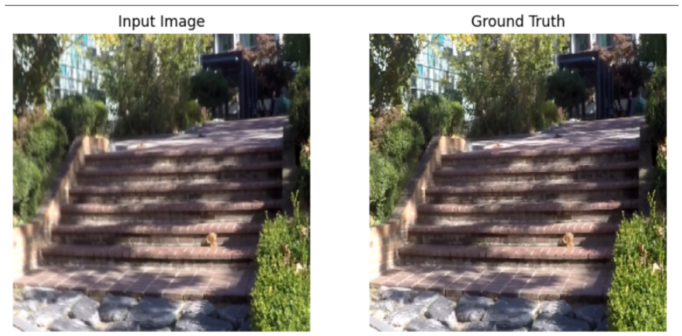

Fig. 2. Image showing some sample images present in the GoPro dataset.

II. Methodology

A. Dataset

The datasets used were taken from https://www.kaggle.com/datasets/jishnuparayilshibu/a-curated-list-of-image-deblurring-datasets/data. From here we selected the CelebA 1 and the GoPro 2 datasets, for the first one, the CNN (Convolutional Neural Networks) deep learning architecture was applied and for the second one, the GANs (Generative Adversarial Networks) architecture.

B. Overall Workflow

Two different workflows were implemented, one for each of the deep learning architectures used. Figure 3 and Figure 4 represent this workflows. For CNNs, we begin with data collection, ensuring a robust and representative dataset for training. This is followed by data preprocessing, where images are normalized and resized to maintain consistency.During the model design phase, we specify the CNN architecture, which includes convolutional, pooling, and fully connected layers, and then compile it with the proper loss functions and optimizers. In the training phase we feed the model with training data and adjust the parameters repeatedly over several epochs while keeping an eye on metrics like accuracy and loss. Then the validation set is used for evaluating the model. Finally, the trained model is deployed for use in production, allowing inference and classification of new data. For GANs, the process also begins with data collection and preprocessing. In the model design phase, both, the generator and discriminator networks are constructed. Training consists of conditioning the discriminator with produced and real data, and fine-tuning the generator to produce realistic outputs based on metrics such as Frechet Inception Distance (FID) and Inception Score (IS). And finally, it is also evaluated with a validation set and then released for use.

III. Results

A. Question 1

To measure how much an image can be improved via deblurring we calculate two different parameters, the PSNR and the SSIM, The PSNR, which means, Peak Signal-to-Noise Ratio is a measure of the quality of signal reconstruction in images and video. It quantifies the ratio between the maximum possible signal and the noise that affects the quality of the signal representation. It is expressed in decibels (dB). A high value of PSNR means that the processed image is very similar to the original one. The SSIM, Structural Similarity Index, is a measure of the similarity between two images. Instead of simply measuring the difference in pixel values like MSE, SSIM considers changes in the structure, luminance and contrast of the images. It provides a better approximation of human visual perception. The values vary between 0 and 1, being 0 a low similarity and 1 high. A little sample of these values can be seen in Figure 5.

B. Question 2

Security, astronomy, and medical imaging have all been significantly impacted by the development of image deblurring technologies. In the medical industry, increasing clarity in CT, MRI, and X-ray scans has made medical analysis and surgical planning easier and resulted in more accurate diagnosis, better anomaly identification, and better patient outcomes. Sharper images of celestial objects taken by telescopes have made it possible to observe and study stars, planets, and galaxies in more detail. This has led to important scientific discoveries in astronomy by enabling the detection and study of far-off astronomical occurrences. The higher resolution photos and videos from surveillance cameras have improved incident analysis, strengthened suspect identification, and given more dependable security monitoring in the field of surveillance and security, supporting law enforcement in their investigations.

C. Question 3

The continuous improvement of image deblurring technology, while beneficial, poses significant dangers and ethical concerns, including privacy invasion, misuse in surveillance and law enforcement, and the creation of deepfakes. Improved capabilities include the ability to extract information from blurry photos, which could reveal private information and result in illegal monitoring and spying that violates people's right to privacy. This technology can help law enforcement with investigations, but it can also cause ethical and legal problems like widespread surveillance, the degradation of civil freedoms, and false positives that result in erroneous accusations. Furthermore, the technology can be used to alter and produce deepfakes and photos, disseminating false information and eroding confidence in visual media.

IV. Discussion

When trying to quantify an image's improvement it is hard to have a standard since it depends on the eye of the observer. In the team's opinion, little improvement was seen. This could be explained by the limited dataset utilized for the experiment. This was the provided dataset so there was no room for a more robust dataset. However, when compared to other people's work in the same area, the teams hypothesis proves to be right. When a bigger, more robust dataset is used, the quality of the deblurred images improves as well. Take DeblurGan study in 2018, here the results specify that PSNR improved by 3-4 dB on benchmark datasets as well as showing superior SSIM scores.

Image deblurring has had a big presence in many areas in the current world including medical imaging, surveillance systems, and photography. When it comes to medical imaging, it helps enhance the clarity of MRI or CT scans which in some cases lead to a more accurate diagnosis. In security surveillance it has seen an improvement when trying to recognize faces, license plates, and different actions performed by the objects. This helps provide a better analysis in important events. The world of photography is where you see the most day-to-day uses. What would have been an unusable photo in the past, it is now possible to try to fix it and make it more suitable for the user to utilize. Given that the current world has a new shift into social media and businesses profit from this, it makes sense for them to invest in good software to help as much as possible with their cause.

Not everything from this technological advancement is positive. This poses a major threat to a person's privacy, possible deepfakes and it also raises ethical concerns since if utilized to its full potential, it can be very dangerous. Since the results are up to interpretation of the observer, it is possible that whatever the software sharpens is not what it, in reality, is. Since this is a visual aid, deepfakes can be created that can damage a person's integrity as well as cause international problems if used on people in positions of power. In the medical field this also brings a possible problem since the software may mistake important anatomical features or pathologies which can lead to a misdiagnosis.

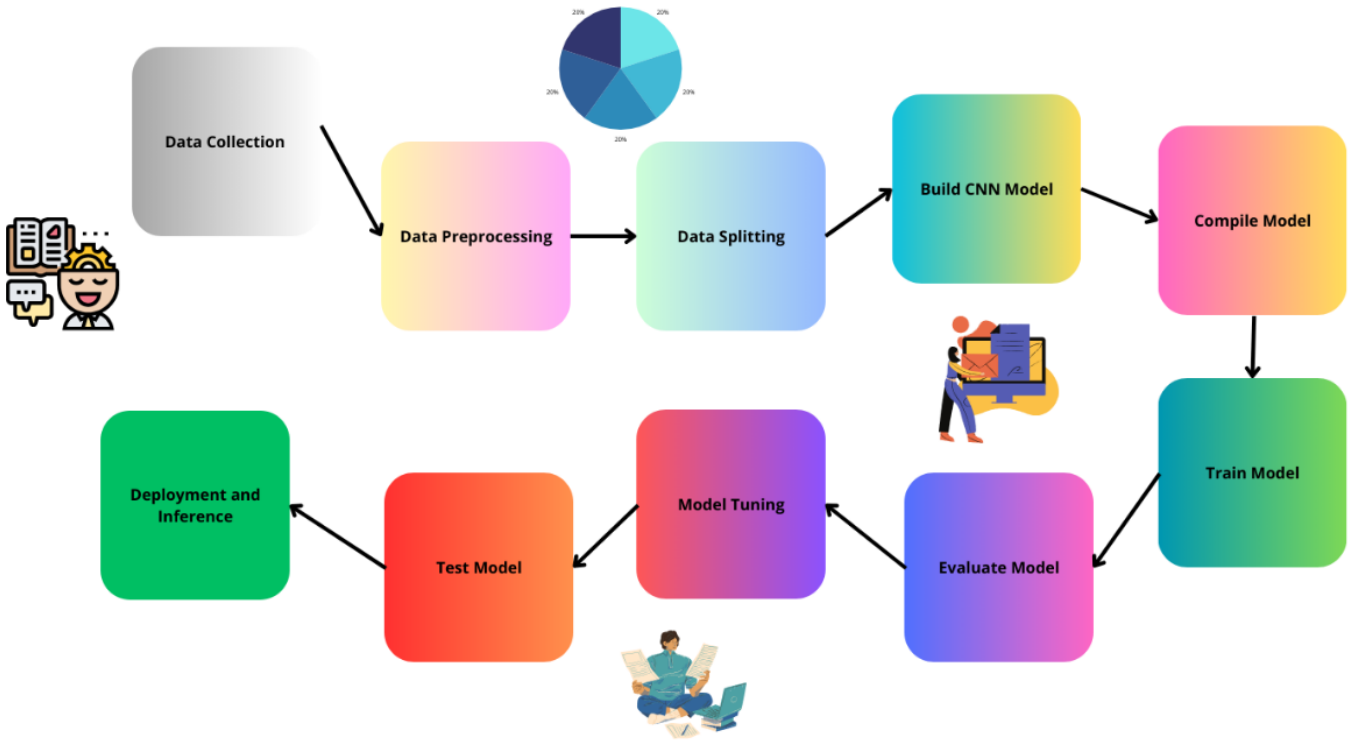

Fig. 3. Figure showing the CNN workflow.

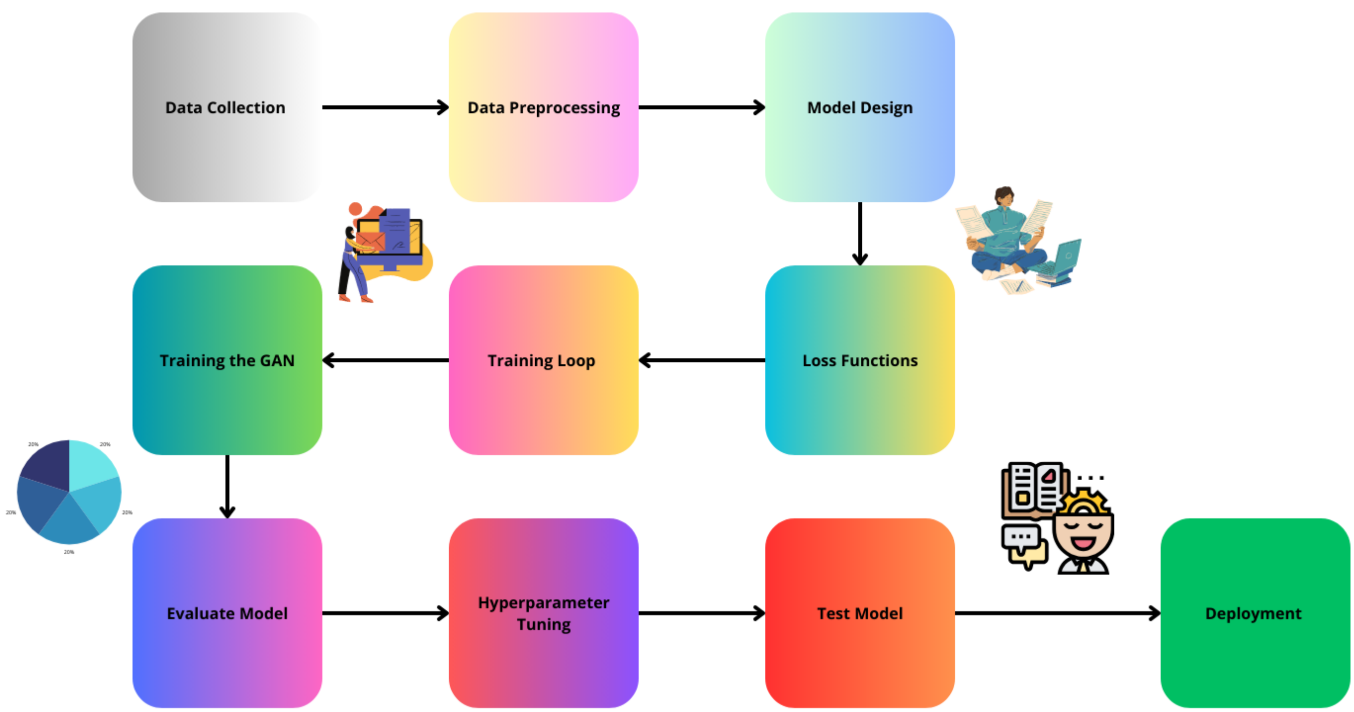

Fig. 4. Figure showing the GANs workflow.

V. Conclusion

To conclude, the whole process is clear on what you need to do in order to achieve what you want. The field is very advanced but there are some areas where improvement is needed promptly. The computational restrictions can put a toll or even hinder the desired results. GAN is a network that pits two programs together to run different tasks in order to produce the best outcome. One for new images and the other

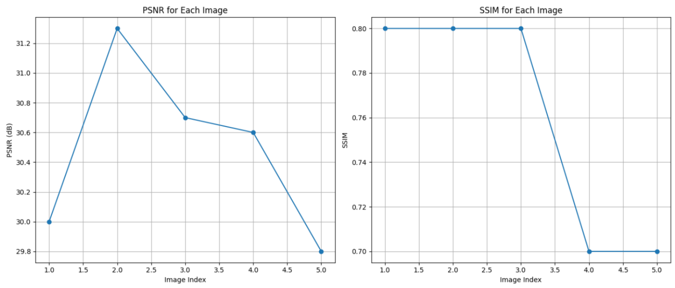

Fig. 5. Results of the CNN architecture.

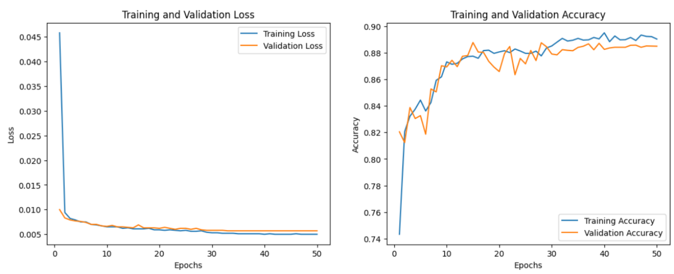

Fig. 6. Results of the CNN architecture.

to test whether the image belongs in the data set or if it is a desired result. CNN is also used in computer vision thanks to its multiple layer approach which makes it easier to process the data carefully. When used in this project, the team found out that they help attain the desired results and have a constant and similar output each time.

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