Introduction

This internship, spanning one month (Apr 22–May 22, 2025), focused on the Colorization Project, which uses deep learning to colorize grayscale images automatically. It was intended to develop and inspect CNN-based colorization models, viewing the layers add color to black-and-white inputs. The model was implemented in the Lab color space: it takes in the lightness (L) channel and predicts the color channels, a usual approach in recent research. This method facilitates end-to-end colorization via neural networks.

Background

Image colorization refers to the process of inserting realistic colors into grayscale or monochrome photographs. Traditionally an artistic, manual task, it is currently done with automated convolutional neural networks (CNNs) and GANs. Deep learning has significantly sped up colorization – CNNs can learn to project a B/W image onto its colored counterpart.Studies indicate that presenting colorization as a learning problem can even enhance understanding of scenes: models that color well tend to represent semantic features such as object categories, texture and depth.

Automated colorization has numerous uses. It enhances the visual and perceptual value of images and video by estimating RGB colors from grayscale frames. For instance, colorization can revive historical photographs and film for museums and education, restore old family photographs, or enhance medical and satellite imagery for easier interpretation. It also is a handy pretext task in computer vision: colored output tends to expose semantic structure of scenes, helping tasks like image segmentation.Shortly, state-of-the-art AI-based colorization can restore and enrich visual data at scale and connect it to larger vision tasks.

Learning Objectives

- Deep Learning Expertise: Develop familiarity with CNN architectures (encoders/decoders) for image-to-image applications and understand when to apply regression vs. classification losses.
- Image Processing: Get experience with image color spaces (particularly Lab), image preprocessing, and feature visualization methods.
- Domain Adaptation: Investigate cross-domain methods (e.g. cycle-consistent GANs) to process such inputs as sketches or infrared images.
- Tools & Frameworks: Build expertise with tools like PyTorch, Jupyter notebooks, and version control (Git/GitHub) in a machine learning process.
- Model Deployment: Practice deploying, training, and testing models, visualizing outputs, and documenting results for sharing and reproducibility.

Activities and Tasks

Task 1: Visualizing the colorization Process

Goal: Expand the colorizer to non-photographic spaces: sketches, infrared satellite images, and other grayscale spaces. The intern designed an extensible framework in which varied input modalities could be colorized. For instance, line-drawing sketches were transformed to lavishly colored art styles, and infrared satellite imagery was translated to normal RGB terrain vision. This involved cross-domain transfer: in other instances, a CycleGAN structure was utilized to transfer between domains without strictly paired samples. Adversarial training allowed the model to generate realistic-colored outputs even when ground truth-colored pairs were missing. This exercise highlighted the flexibility of the network: through training on heterogeneous datasets, it was possible to both colorize ordinary images and ideally transform sketches and IR images into realistic color images.

Task 2: Colorization of Historical Photos

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Task 3: Cross-Domain Image Colorization

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Skills and Competencies

- Deep Learning & Models: Enhanced skill to develop and train CNN/U-Net models and conditional GANs for image-to-image translation tasks.
- Data Processing: Acquired experience in image preprocessing, such as grayscale-to-Lab conversion, resizing, normalisation, and data augmentation.
- PyTorch & Python: Built experience in PyTorch for network construction, training loops, and model inference, and utilisation of Jupyter notebooks for prototyping and visualisation.

- DomainAdaptation: Acquired domaintransfer methods such as CycleGANs for manag ing unpaired image domains, enhancing model generalization across inputs.
- Software Tools: Enhanced version control (Git/GitHub) proficiency for project collaboration and tracking and Python libraries (e.g. NumPy, OpenCV, matplotlib) for computer vision.
- Soft Skills: Improved project management (time-planning within a one-month deadline), technical documentation, and communication with mentors.

Feedback and Evidence

Mentors gave iterative feedback on model performance, including recommendations for network depth and training approach. For evidence of progress, the GitHub repository indicates active development: 32 commits record code contribution and experimentation over the internship. The project deliverables (Jupyter notebooks, Python scripts) are all version controlled on GitHub. Sample outputs (colorized images for each task) were also presented to supervisors. For example, intermediate visualizations and last colorized images were incorporated within reports, showcasing enhanced color quality after adding historical references and domain adaptation using GANs. This recorded workflow and observable commit history represent tangible proof of the work done.

Challenges and Solutions

Color Ambiguity: One of the key difficulties was that colorization is naturally under-constrained (there are many acceptable colors for a given object). Early models would regress to "safe" desaturated colors. To mitigate this, classification-based losses and GANs were employed, prompting the model to generate more saturated, realistic colors.

Historical Color Accuracy: Period-specific color in historical photographs is hard to achieve because of insufficient precise ground truth. This is countered by studying the common color schemes of the time and manually adjusting the model output. Practically, the model output was corrected with color transfer from similar-era reference images.

Domain Gaps: Colorizing inputs such as sketches and infrared images was a domain shift issue. We overcame this using cycle-consistent GANs to translate across domains without paired domain. This enabled the model to learn mappings (i.e. from infrared to visible-spectrum imagery) by imposing consistency cycles.

Limited Data: With a month and limited training data, it was difficult to produce good results. Techniques from more recent tutorials were used: aggressive data augmentation and effective architectures (e.g. U-Nets with skip connections) allowed training with smaller datasets within reasonable time. This allowed the intern to achieve useful results under limited resources.

Outcomes and Impact

The internship produced a number of deliverables and learnings. All three tasks produced working colorization pipelines:

Visualized Process: Illustrated how the CNN gradually adds color, as an educational tool for learning about deep models.

Historical Colorization: Produced colorized records, rendering historical scenes more realistic (useful for museums or digital archives). This complies with research indicating that colorization enables people to become more invested in history.

Cross-Domain Model: Created a generalizable model that could accommodate diverse inputs (sketches, satellite IR), which could be tuned for use in future remote sensing or digital art projects.

In terms of real-world application, these findings set the stage for practical uses (e.g. automated photo restoration, artistic sketch stylization software). The project further advances image translation research: training without paired examples (through CycleGAN) provides evidence of a scalable solution where annotated data are limited.

Conclusion

This internship exposed one fully to deep-learning based image colorization. The intern was able to successfully execute major tasks, developing CNN and GAN models to colorize an image and studying their behavior. Through the project, the intern was able to witness firsthand how deep neural networks are capable of inferring automatically color and scene semantics from luminance only. The major takeaways are mastering Lab-color models, visualizing neural outputs, and the might of adversarial training for domain adaptation. By and large, the exercise enriched technical know-how in computer vision and machine learning and illustrated the thrilling potential of colorization to facilitate image understanding and preservation. Sources: The foregoing text is based on recent literature and tutorial guides on deep image colorization and is drawn from the project's GitHub documentation.