# UNIVERSITY of MICHIGAN – DEARBORN

## CIS 583  DEEP LEARNING

# MID-TERM PROJECT REPORT

**Section - 001**

**Semester - Winter 2025**


**Team 3**

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# Colorize black and white images


## Abstract:

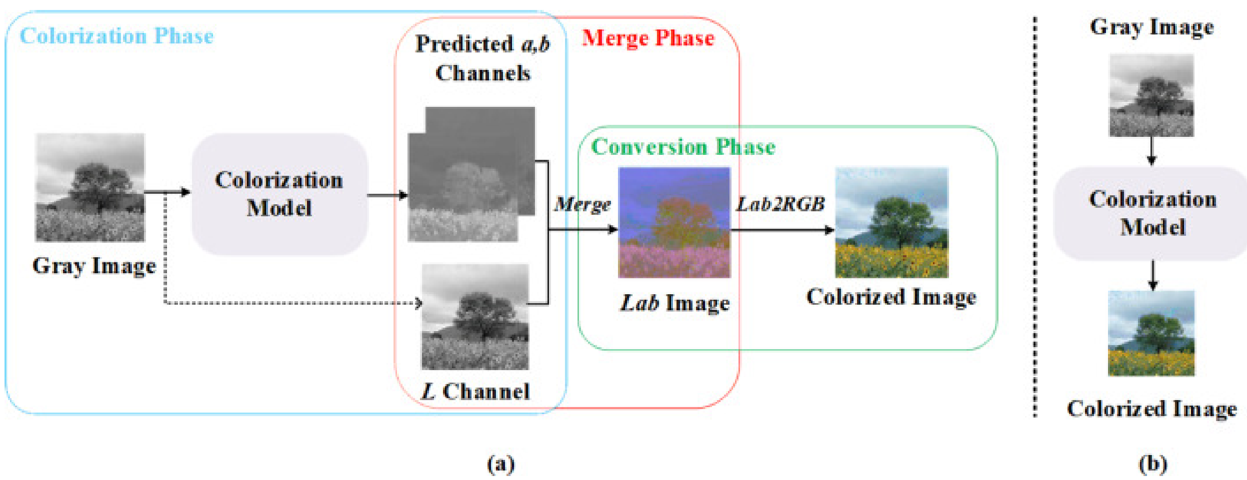
The idea or aim of the project is to develop a deep-learning model for coloring the grayscale pictures, mainly the old photos. Our dataset consists of various landscape elements such as streets, buildings, mountains, glaciers, and trees and their matched grayscale versions are placed into separate folders. The dataset which we are using from that we are going to train an autoencoder to make our model learn how to map between grayscale and color images, making the model to predict accurate colourizations. For the selected topic it is supervised learning, in which we are pairing the grayscale and the corresponding color picture data to train the model. The main goal is to produce a working prototype which shows that automated picture colorization is possible and can be sufficiently accurate. For achieving accurate results, this project involves the preprocessing of the dataset creating a Convolutional Auto-encoder structure.

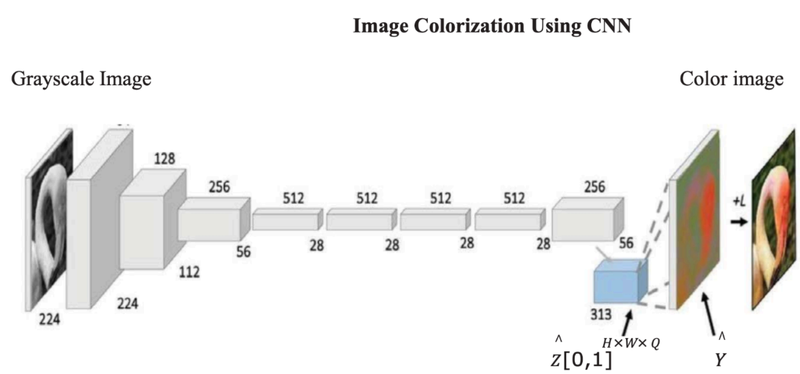
This project uses supervised learning, training on paired grayscale and color images. The trained model can improve grayscale images, helps the applications in image restoration, artistic generation, and historical image improvement. Through this project, the potential of deep learning in automating the colorization process while improving generalization across varied landscape settings by using CNN-based approaches for exploratory analysis and visualization and structuring the model for future end-to-end training will be explored. The model learns to predict color parts from an image's brightness by using convolutional auto-encoders. Finally, the results will aim to show the capacity of deep learning techniques to automate the picture colorization process in various situations. This has varied applications in image restoration, creative production and historical image analysis.


## Problem Statement:

Copious amounts of old, personal and important photographs are in grayscale and have lost quality over time due to various factors like technology, noise, preservation inefficiencies and plain aging. Our goal is to preserve and enhance the visual quality of historical and legacy images through deep learning convolutional neural networks. While technological advancements have made it extremely effortless to capture great color images today, countless photographs from the past are limited to black-and-white images. In the last decade, technological improvements have made it possible for people to capture and store high-quality color images with just a click on their phones. However, older grayscale images, though historically significant, often fail to convey the depth, emotion and actuality that color can provide.

We selected this topic because it sits at the intersection of visual storytelling, computer vision and AI-driven creativity. Automatically colorizing black-and-white images not only improves their visual appeal but also contributes to cultural preservation, digital media restoration and user engagement in creative applications. This project idea is to fill the gap by creating a deep learning-based solution to automatically convert grayscale images into color. By leveraging CNN-based Autoencoders, GANs (DeOldify), and U-Net architectures, we seek to create a scalable and efficient approach to restoring and enhancing black-and-white images. Through this project we want to evaluate different color spaces, preprocessing techniques and augmentation strategies that contribute to the model's accuracy and generalizability.



**Background and AI Type :** The core image colorization task involves generating a color image from grayscale input. The model to achieve this learns to map pixel intensities from grayscale domain the color domain. Due to the availability of paired data in the dataset, this problem is best approached using Supervised Learning.

## Tools and technologies used:

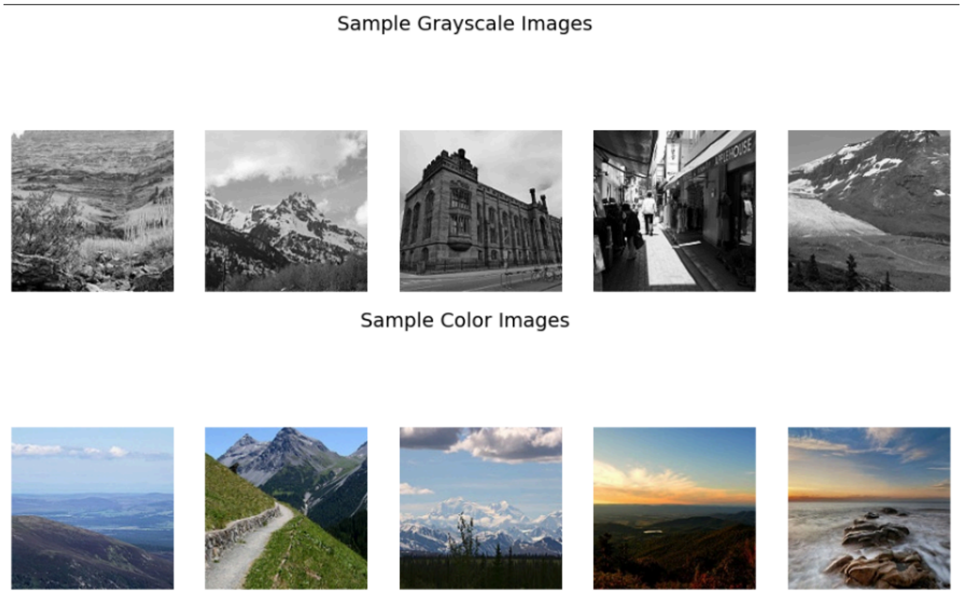
- Programming language: Python
- Deep learning Techniques : Pytorch, TensorFlow, Keras
- Image processing and color space manipulation : OpenCV
- Libraries : NumPy, Pandas, Matplotlib, Seaborn, Scikit-image
- Dataset Source and versioning : Kaggle API
- Platform: Google Colab

## Dataset:

Source :
https://www.kaggle.com/datasets/theblackmamba31/landscape-image-colorization/data

**Data Description:** The dataset consists of **7,219 images**, each available in grayscale and color variations. These images cover a variety of categories such as streets,buildings,mountains,glaciers , trees etc, making it ideal for training deep learning models to understand color distributions. The dataset is well-suited for supervised learning as it contains grayscale and color versions of each image and the validation set is readily available. The images are in JPG and PNG formats. The structure mainly consists of two folders which are /gray which contains the grayscale versions and /color which contains the corresponding color versions. The resolution and size of these images vary. Pre-processing is done to resize them to consistent dimensions. These images are high resolution with good lighting, contrast and sharpness in most of the samples. The RGB histograms are well-distributed which are ideal for color prediction modeling.

The dataset is ideal for learning color mappings due to its resize, diversity and high quality this make it straightforward to build supervised learning pipelines. During Exploratory Data Analysis (EDA) the dataset exhibited good Distribution in Aspect Ratios, Image sizes, and RGB channel distribution.



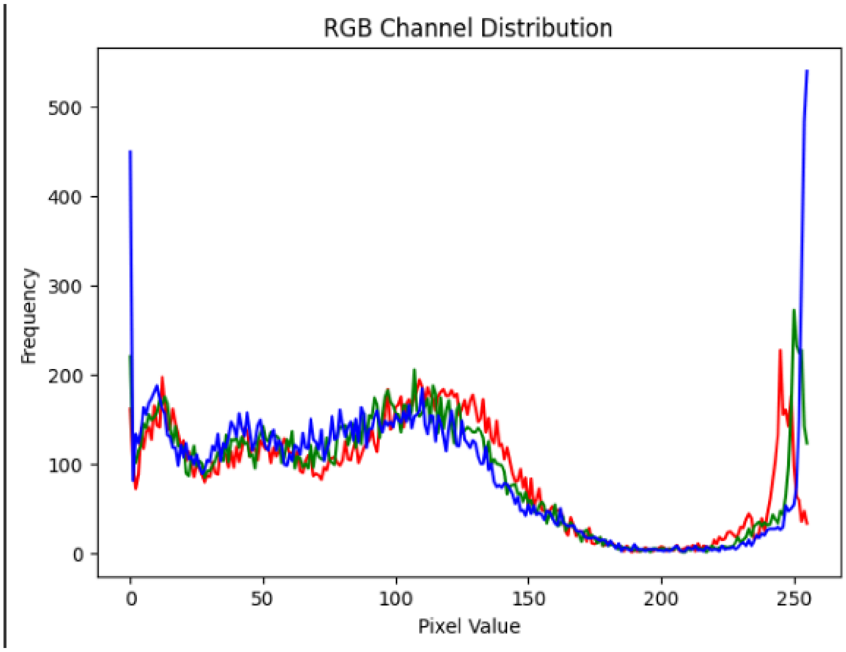

**Sample Image of Color and gray-scale.**

| | Height | Width | Channels | Aspect Ratio |
|---|---|---|---|---|
| 0 | 150 | 150 | 3 | 1.0 |
| 1 | 150 | 150 | 3 | 1.0 |
| 2 | 150 | 150 | 3 | 1.0 |
| 3 | 150 | 150 | 3 | 1.0 |
| 4 | 150 | 150 | 3 | 1.0 |

Descriptive Statistics:

| | Height | Width | Channels | Aspect Ratio |
|---|---|---|---|---|
| count | 14258.000000 | 14258.0 | 14258.0 | 14258.000000 |
| mean | 149.886800 | 150.0 | 3.0 | 1.001206 |
| std | 2.414321 | 0.0 | 0.0 | 0.028389 |
| min | 72.000000 | 150.0 | 3.0 | 1.000000 |
| 25% | 150.000000 | 150.0 | 3.0 | 1.000000 |
| 50% | 150.000000 | 150.0 | 3.0 | 1.000000 |
| 75% | 150.000000 | 150.0 | 3.0 | 1.000000 |
| max | 150.000000 | 150.0 | 3.0 | 2.083333 |

**Descriptive statistics**




**RGB Channel Distribution**

**Data Acquisition Challenges :** While the dataset was comprehensive, several challenges were encountered during the acquisition and preparation phases such as :

- Manual upload of the kaggle.json API key in Google Colab was necessary requirement hindering auto processing
- The folder names with spaces required careful path handling and regex mapping in code.
- We need to make sure that the grayscale and color folders were correctly aligned in terms of filenames to enable supervised learning.
- Images came in varying resolutions and aspect ratios so all the images were resized to a standard size using OpenCv.
- LAB color space was used to separate luminance from chrominance.This required normalization of L channel normalized to [0,1] and a and b channels scaled to [-1,1]

**Model Overview:**

For this project, we are designing a convolutional auto-encoder model that learns to colorize grayscale images using supervised learning. The model input is in grayscale image and the output is the predicted a and b chrominance channels in LAB color space. The final colorized image is reconstructed by combining the original L-channel with the predicted a/b channels and converting the LAB image back to RGB. This architecture comprises only CNN based auto-encoder and we are planning to use an U-Net based approach for the final presentation. The ML framework used is PyTorch with OpenCV and NumPy for preprocessing.

**Results:**

We performed extensive exploratory analysis and visual "*human-eye"* validation of the data before preprocessing. The outcomes from the mid-term stage are as follows:

- For LAB color Space Validation, we performed a full round-trip conversion of RGB→LAB→RGB. The reconstructed images were visually similar to the originals which proves that the color space handling is accurate. This output tells the LAB normalization and scaling methods are correct.
- Generated histograms of image height, width, aspect ratio and pixel brightness. RGB channel distribution showed natural variability with no spikes across landscape images.
- The L-channel normalized to [0,1] , a/b channels scaled to [-1,1] where the images successfully reassembled normalized LAB channels into RGB images using OpenCV.

Next steps to enhance model accuracy are to firstly train the autoencoder on the preprocessed LAB dataset. Then by adding connections ( u-Net). Evaluating SSIM and PSNR to measure reconstruction quality and to also use fine-tune model using more advanced architectures like DeOldify which is GAN-based.

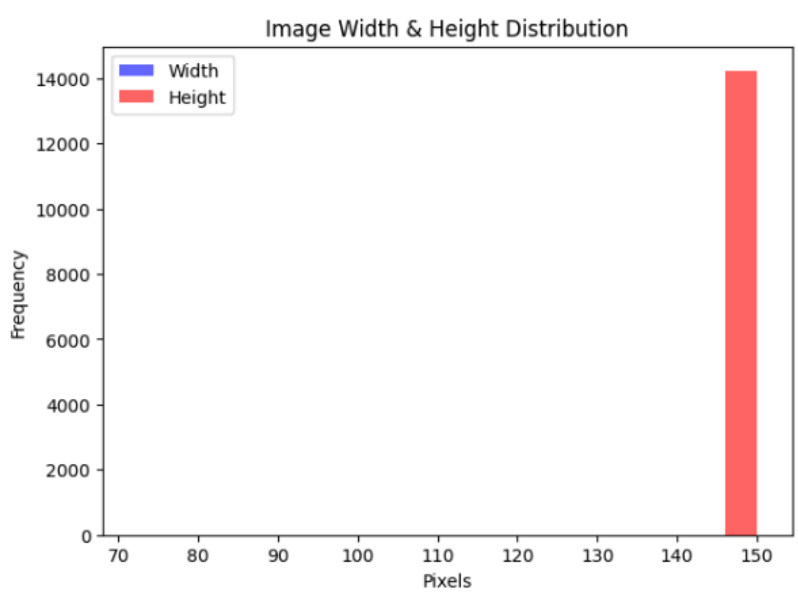
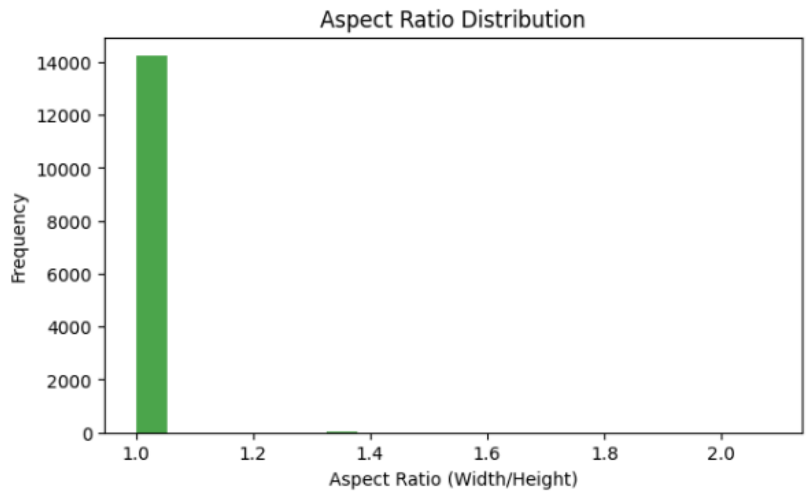
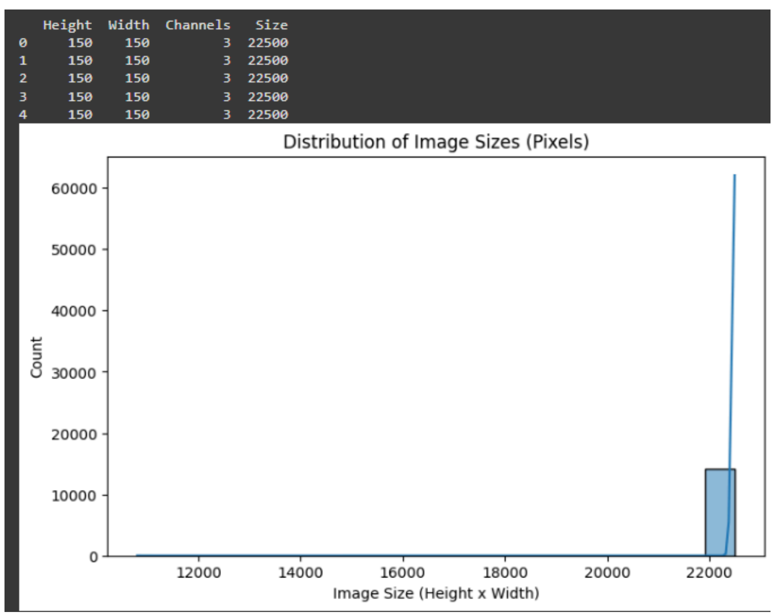



**Image Width & Height Distribution**



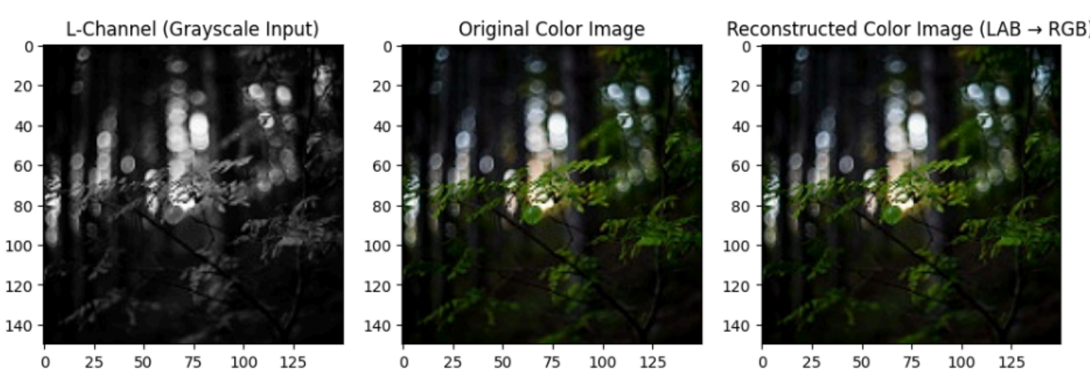

**Aspect Ratio Distribution**



| | Height | Width | Channels | Size |
|---|---|---|---|---|
| 0 | 150 | 150 | 3 | 22500 |
| 1 | 150 | 150 | 3 | 22500 |
| 2 | 150 | 150 | 3 | 22500 |
| 3 | 150 | 150 | 3 | 22500 |
| 4 | 150 | 150 | 3 | 22500 |



**Distribution of Image Size**




**L-channel Input and Output**

# Conclusions:

**Project Impact:** This project addresses a practical and culturally significant challenge of restoring grayscale images to their original color.. Colorization has scientific relevance in historical preservation, artistic enhancement, journalism and digital media restoration. By automating this process, this project aims to contribute to the democratization of visual content restoration, making it accessible to a broader audience without the need for extensive technical know-how or spending large amounts of money.

From a technical standpoint, this project also demonstrates how deep learning and image processing can be combined to solve real-world computer vision problems. It opens up pathways for using similar architectures in domains such as medical imaging,, where grayscale-to-color mapping is often applied to enhance interpretability. On a societal level, colorizing historical and archival images can help younger generations better relate to past events, bridging emotional and generational gaps and also get a sense of how their ancestors lived. This project can also serve as an educational and cultural tool in various settings.

**Future Plans in Expanding the Project :** We foresee the next phase of the project to focus on training, validating and refining the autoencoder model, followed by exploring advanced architectures. The expansion areas are as follows :

- Training the convolutional encoder on the LAB converted dataset, by implementing performance evaluation metrics such as PSNT, SSIM etc.
- By extending U-Net to preserve edge features and textures.
- Integrating DeOldify which is a GAN based approach for photorealistic results and comparing the CNN and GAN based performance to further optimize the model.
- Expanding the dataset with more diverse scenes, including people, animals and historical monuments and potentially incorporate domain specific dataset for specialized use cases.

# Summary:

**Reflection on the Project :**

Working on this project provided an insightful and rewarding experience in the field of computer vision and deep learning with a lot of learning opportunities along the way.One of the most enjoyable aspects was seeing the transformation of grayscale images into colorized outputs using LAB color space conversion. Hence the ability to reconstruct and visualize images based on channel manipulation deepened our comprehension of image manipulation beyond traditional RGB formats. We were surprised by how effective the LAB space was in segregating luminance from chrominance thereby making it easier to conceptualize the learning problem for the model. During the preprocessing phase which included texture analysis and normalization, provided hands-on opportunity for all the team members to bridge theoretical concepts with practical implementations.

The most challenging part was handling the different image alignments and preprocessing thousands of files to ensure consistency. An equally difficult task was before preprocessing, we had to come up with an effective strategy to design the preprocessing architecture to ensure consistency in image format and image quality. However this brought about a greater understanding of the importance of data consistency & quality in AI projects.

We are extremely proud of the thorough exploratory data analysis(EDA) and the development of a complete preprocessing pipeline which included LAB transformation and reconstruction verification which sets a strong technical foundation for the model training phase for the final submission.

## Project Overview:

As mentioned earlier, this project explores the use of deep learning to automate the colorization of grayscale images by using a comprehensive dataset with matching grayscale and color landscape, photographs. Throughout the last couple of months, we built a comprehensive pipeline that preprocesses and prepares the data for supervised learning model training. We leveraged LAB color space to separate luminance and chrominance, facilitating the design of a convolutional auto-encoder architecture. Now, the goal is to further train this model to learn mappings from grayscale to color, enabling automatic color restoration of black-and-white images without the use of supervised learning.

Our work included dataset preparation, statistical and visual analysis and preliminary model structuring and data definition. In the final phase, we aim to train and evaluate the model while also experimenting with advanced architectures like U-Net and GANs to explore potential improvements in performance.

Working as a team has been very beneficial. Each member contributed to a core part of the project which is data processing, visualization, model pipeline and documentation.Collaborative brainstorming helped us immensely by addressing product and technical challenges more effectively and dividing the task efficiently and to maintain a consistent project direction. The teamwork helped foster a productive environment where learning and development were shared equally among all team members and everybody pitched in when the other was not available.

## Roles and responsibilities:

| Sno | Team Member | Responsibility |
|---|---|---|
| 1 | Pranavi Annae | • CNN-Based Autoencoder |
| 2 | Rahul Sai Sudeer Vadala | • DeOldify (GAN-Based Approach) |
| 3 | Sindhuja Gandi | • U-Net-based image Colorization |
| 4 | Sundar Swaminathan | • Error Analysis and Retraining using Hyperparameter tuning(CNN) |

## References:

[1] A. Author, B. Author, and C. Author, "Automatic colorization of black and white images using convolutional neural networks," *ResearchGate*, Nov. 2021. Available: https://www.researchgate.net/publication/356705435_Automatic_colorization_of_black_and_white_images_using_convolutional_neural_networks/citation/download

[2] V. Raghavan, S. Rupa Sree, K. R, S. Hariharan, and B. A, "Black and White Image Colorization using Deep Learning," 2022 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON), Bengaluru, India, 2022, pp. 27-30, doi: 10.1109/CENTCON56610.2022.10051533. Available: https://ieeexplore.ieee.org/document/10051533

[3] I. Akarawita and A. M. H. S. Abeykoon, "Automatic Colorization of Greyscale Images Using Deep Learning Fusion Technique and Accuracy Level Analysis," 2024 International Conference on Advanced Robotics and Mechatronics (ICARM), Tokyo, Japan, 2024, pp. 625-630, doi: 10.1109/ICARM62033.2024.10715939. keywords: {Training;Visualization;Accuracy;Gray-scale;Predictive models;Prediction algorithms;Production facilities;Heat maps;Tuning;Robots},

[4] Singh, V., Arora, D., Sharma, P. (2022). Image Colorization Using Deep Convolution Autoencoder. In: Mahapatra, R.P., Peddoju, S.K., Roy, S., Parwekar, P., Goel, L. (eds) Proceedings of International Conference on Recent Trends in Computing . Lecture Notes in Networks and Systems, vol 341. Springer, Singapore. https://doi.org/10.1007/978-981-16-7118-0_37