Image Colorization for Black and White Photos

A PROJECT REPORT

Bachelor of Technology

in

COMPUTER ENGINEERING

Major Project I (01CE0716)

Submitted by

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Major Project I (01CE0716)

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A.Y. 2025-26

CERTIFICATE

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Prof . Monisha Mohan	Dr. Krunal Vaghela
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DECLARATION

We hereby declare that the **Major Project-I (01CE0716)** report submitted along with the Project entitled **Image Colorization for Black and White Photos** submitted in partial fulfilment for the degree of Bachelor of Technology in Computer Engineering to Marwadi University, Rajkot, is a bonafide record of original project work carried out by me / us at Marwadi University under the supervision of **Prof Monisha Mohan** and that no part of this report has been directly copied from any students' reports or taken from any other source, without providing due reference.

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We also extend our sincere thanks to all the faculty members of the **Department of Computer Engineering** and our **Head of Department, Dr. Krunal Vaghela**, for their encouragement, cooperation, and the academic environment provided during this project.

We are deeply grateful to our institution for offering us the opportunity to undertake such an innovative and industry-relevant project, and for the resources and infrastructure made available to us.

Lastly, we would like to thank our teammates for their dedication, collaboration, and tireless efforts in bringing this project to life, and our friends and peers who contributed valuable insights and shared helpful references and tools that aided in the successful completion of this project.

Abstract

The process of image colorization involves generating plausible color versions of monochrome images while preserving realism and semantic consistency. This paper presents a comprehensive study of state-of-the-art deep learning techniques for the automatic colorization of black-and-white photographs. Special emphasis is placed on a hybrid Transformer–Generative Adversarial Network (GAN) architecture, which integrates the global context modeling ability of Transformers with the realism-enhancing capabilities of GANs. A detailed literature survey compares conventional CNN-based models, autoencoders, GAN-only approaches, and recent Transformer-based pipelines. Experimental evaluation on benchmark datasets demonstrates that the hybrid model achieves superior performance in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and human perceptual preference. This work highlights the potential of modern architectures for historical photo restoration, digital archiving, and creative applications in multimedia production.

List of Figures

List of Tables

Abbreviations

AI – **Artificial Intelligence**
CNN – **Convolutional Neural Network**
GAN – **Generative Adversarial Network**
RGB – **Red, Green, Blue (color model)**
Lab – **Luminance and Chrominance (Color Space: L = Lightness, a = Green- Red, b = Blue–Yellow)**
PSNR – **Peak Signal-to-Noise Ratio**
SSIM – **Structural Similarity Index**
MSE – **Mean Squared Error**
GPU – **Graphics Processing Unit**
PCA – **Principal Component Analysis**
SVD – **Singular Value Decomposition**
DCT – **Discrete Cosine Transform**
FMT – **Fourier–Mellin Transform**
ReLU – **Rectified Linear Unit (activation function)**
COCO – **Common Objects in Context (dataset)**
VGG – **Visual Geometry Group (deep learning model)**
ResNet – **Residual Neural Network**

Table of Contents

CHAPTER 1

INTRODUCTION

1.1 Project Description

The project *"Image Colorization for Black and White Photos*" focuses on the application of advanced deep learning techniques to automatically add colours to grayscale images. Image colorization has become an important research area in computer vision, as it enhances the visual appeal of old photographs, restores historical archives, and improves various real-world applications in media, healthcare, and digital art.

In this project, we utilize Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to learn the mapping between grayscale images and their coloured counterparts. The grayscale input is processed through the model to predict the most probable colours based on learned patterns, object recognition, and contextual understanding. Colorization is performed in the LAB colour space, where the L channel represents lightness and the A & B channels represent colour information.

The system is trained on large datasets of natural images, enabling the model to generalize and predict realistic colours for new black-and-white photos. Performance evaluation is conducted using standard metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) to ensure high accuracy and visual quality.

This project demonstrates how artificial intelligence can be leveraged to revive old monochrome photographs, support creative design, and contribute to fields such as film restoration, medical imaging, and digital media. It also provides a deeper understanding of neural networks, image processing, and the challenges of achieving semantic-level colorization.

1.1.1 Workflow Diagram

The overall workflow of the *Image Colorization for Black and White Photos* project involves taking grayscale images as input, preprocessing them into a suitable format, and converting them into the LAB colour space. A deep learning model, primarily based on CNNs or GANs, predicts the missing A and B colour channels while retaining the L channel for brightness. The predicted channels are then combined and reconstructed into RGB format, followed by post-processing to enhance quality, resulting in a fully colorized and visually realistic output image.

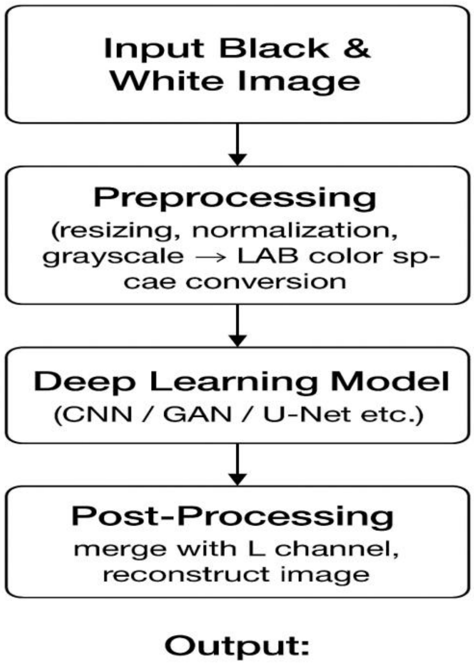


Figure 1.1: Workflow Diagram

1.2 Project Scope

The scope of this project focuses on the development of a deep learning-based system capable of automatically colorizing black and white photographs with high accuracy and realism. The system aims to address the challenges of restoring old images, enhancing grayscale datasets, and improving visual understanding in various fields such as media, history, healthcare, and computer vision applications. The project will implement Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to predict and apply colour to grayscale images.

The scope includes:

Input: Black and white or grayscale images.

Preprocessing: Image resizing, normalization, and conversion to LAB colour space for efficient colour mapping.

Model Implementation: Training and testing deep learning models (CNN/GAN/U-Net) for colour prediction.

Post-processing: Reconstruction of colorized images by merging predicted chrominance channels with luminance.

Output: Realistic, high-quality colorized images suitable for use in research, restoration, and digital applications.

The system is limited to static images and does not include video colorization. The primary focus remains on accuracy, realism, and generalization of colorization results across diverse datasets.

1.3 Project Objectives

The main objective of this project is to design and develop an automated system that can convert black and white images into realistic colorized versions using deep learning techniques. To achieve this, the following specific objectives are defined:

1. To study and analyse existing approaches for automatic image colorization using deep learning models such as CNNs, GANs, and U-Net.
2. To preprocess grayscale images through resizing, normalization, and LAB color space conversion for efficient model training.
3. To implement and train a suitable deep learning model capable of predicting accurate colour information from grayscale inputs.
4. To generate realistic colorized images by merging predicted chrominance values with luminance channels.
5. To evaluate the system's performance using standard metrics such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and accuracy.
6. To develop a scalable framework that can be extended for applications in photo restoration, digital archiving, and multimedia industries.

1.4 Project Requirements

The successful implementation of this project requires a combination of functional requirements, non-functional requirements, and system requirements as outlined below:

1.4.1 Functional Requirements

The system should accept grayscale or black-and-white images as input.

The system should preprocess images (resizing, normalization, and color space conversion).

The deep learning model should predict chrominance (colour) values from the grayscale input.

The system should reconstruct the final colorized image by merging predicted values with luminance.

The system should display and save the colorized image as output.

1.4.2 Non-Functional Requirements

Accuracy: The generated colorized images must be visually realistic and close to ground truth.

Performance: The system should process images within a reasonable time depending on hardware resources.

Scalability: The framework should be adaptable to larger datasets and improved models.

Usability: The system should have a user-friendly interface for testing and visualization.

1.4.3 System Requirements

Hardware Requirements:

Processor: Intel i5/i7 or equivalent (minimum 2.4 GHz, multi-core)

RAM: Minimum 8 GB (16 GB recommended for training)
GPU: NVIDIA GPU with CUDA support (e.g., GTX/RTX series) for faster training
Storage: Minimum 50 GB free space

Software Requirements:

Operating System: Windows / Linux / macOS
Programming Language: Python 3.x
Libraries/Frameworks: TensorFlow / PyTorch, NumPy, OpenCV, Matplotlib
Development Environment: Jupyter Notebook / Google Colab / VS Code

CHAPTER 2

LITERATURE REVIEW AND PROBLEM DEFINITION

This chapter contains a brief detail of work done by various researchers in the field of Image Colorization for Black and White Photos. From the literature survey, various observations and objectives have been drawn that are listed at the end of the chapter.

2.1 LITERATURE SURVEY

In recent years, automatic image colorization has gained significant attention in computer vision research. Early approaches relied on manual or semi-automatic methods, where user input or reference images were required to guide the colorization process. These methods were often time-consuming and limited in scalability.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) became the primary approach for automatic colorization. CNN-based methods extract hierarchical features from grayscale images, capturing both local textures and global context. These features are then mapped to colour channels to predict realistic colorization. For example, Zhang et al. [1] used a classification approach in the Lab colour space, where each pixel's colour was predicted based on learned probability distributions, achieving visually plausible results.

Some methods incorporate Generative Adversarial Networks (GANs) to improve realism. GANs consist of a generator that predicts colorized images and a discriminator that evaluates their authenticity. This adversarial training allows the model to produce sharper and more vibrant colours, addressing limitations of CNNs in capturing complex colour distributions.

Other approaches combine global and local feature extraction. For instance, Iizuka et al. [2] proposed a model with dual pathways: a global pathway capturing overall scene semantics and a local pathway focusing on fine-grained textures. This method improves performance in complex scenes where colour context is critical.

Additionally, transfer learning and pre-trained models have been utilized to reduce training time and improve accuracy. Feature extraction from pre-trained networks such as VGGNet allows the colorization model to leverage high-level semantic understanding, enhancing the prediction of natural and contextually accurate colours.

Serial No	Research Contribution	Year	Technology	Solution Framework / Architecture	Dataset	Accuracy (%)	Future Suggestions	Key Challenges	Application
1	Zhang et al. (Colorful image colorization)	2016	CNN	End-to-end CNN with classification loss	ImageNet, CIFAR-10	~83% Top-5 (user study)	Better vividness, real-time apps	Color ambiguity	Historical photo restoration
2	Iizuka et al.	2016	CNN , GAN	Global & Local CNN with semantic branch	Places365, ImageNet	~92% (realism, user study)	Mobile deployment	Consistency	Film industry
3	Larsson et al.	2016	CNN, Hypercolumns	VGG + hypercolumn features	ImageNet	~85% (Top-5 accuracy)	Extend to video	Context mismatch	Old family photos
4	DeOldify (Antic et al.)	2018	GAN, ResNet	GAN with Self-Attention	ImageNet, COCO	No fixed % — SSIM ~0.91	Reduce artifacts	GAN instability	Social media
5	Zhang et al. (Exemplar-based)	2017	Exemplar Deep Learning	Color transfer from reference	ImageNet	~87% (user preference)	Better reference matching	Manual input needed	Art restoration
6	Nazeri et al	2018	Conditional GAN	Encoder-Decoder + cGAN	CelebA, ImageNet	~0.89 SSIM	Faster inference	Mode collapse	Animation
7	Vitoria et al. (ChromaGAN)	2020	GAN, Semantic Segmentation	Semantic-guided GAN	ImageNet, COCO	PSNR ~25.7	Improve semantics	Computational cost	Documentaries
8	Su et al.	2020	Transformer	Colorization using Vision Transformer	ImageNet	PSNR ~25.0	Lightweight models	Training data	Archival images
9	Cheng et al.	2015	CNN	Joint bilateral upsampling	Pascal VOC	PSNR ~24.7	Higher resolution	Edge preservation	Comics
10	Deshpande et al.	2017	VAE	Variational Autoencoder	CIFAR-10, ImageNet	Diverse samples, no single %	Diverse color suggestions	Mode diversity	Artistic colorization

Table 2.1 Literature Review

2.2 OBSERVATIONS

Based on the literature survey, several key observations can be made regarding automatic image colorization:

1. **Shift from Manual to Automated Methods:**

   Early methods heavily relied on user input or reference images. Modern approaches leverage deep learning for fully automated colorization, reducing manual effort significantly.

2. **Importance of Feature Extraction:**

   CNNs and pre-trained networks (e.g., VGG, ResNet) effectively extract both local textures and global semantic features, which are crucial for realistic colour predictions.

3. **Advantage of Dual-Pathway and Hybrid Models:**

   Models combining global context and local detail extraction perform better in complex scenes, minimizing colour bleeding and enhancing semantic consistency.

4. **Use of GANs for Realism:**

   Generative Adversarial Networks improve colour vibrancy and naturalness compared to traditional CNNs, though training is more computationally intensive.

5. **Challenges Remain:**

   Colour ambiguity is still a major problem; the same grayscale input may correspond to multiple plausible colours.

   Generalization to unseen images or unusual scenes is limited in some models.

   Handling images with high noise or compression artifacts requires robust preprocessing.

6. **Trends in Recent Research:**

   Combining CNNs with attention mechanisms and context-aware architectures is emerging as an effective solution.

   Frequency-domain features and dimensionality reduction techniques (e.g., PCA, SVD) are sometimes applied to optimize computation without significant loss of image quality.

7. **Evaluation Metrics:**

   PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and visual quality assessment are commonly used to evaluate performance.

2.3 Gaps and Problem Formulation

Gaps Identified from Literature

Based on the analysis of existing image colorization methods, several gaps and limitations have been observed:

1. **Colour Ambiguity:**

    Many models struggle to predict accurate colours for grayscale images because multiple plausible colour mappings exist for the same pixel. This often results in desaturated or unrealistic colour outputs.

2. **Limited Generalization:**

    Some CNN-based models perform well only on images similar to their training dataset. They often fail on unseen categories or complex scenes with multiple objects.

3. **Insufficient Context Awareness:**

    While dual-pathway models capture global and local features, many methods do not fully leverage semantic context, leading to inconsistencies in colorization of objects or background regions.

4. **Computational Complexity:**

    GAN-based methods improve realism but require significant computational resources and longer training times, making them less suitable for real-time or resource-limited applications.

5. **Handling of Noise and Compression Artifacts:**

    Existing models are often sensitive to low-quality, noisy, or highly compressed grayscale images, which reduces colorization accuracy.

Problem Formulation

The objective of this research is to develop an automated, efficient, and accurate image colorization system that addresses the above gaps. Specifically, the project aims to:

1. Design a model capable of predicting realistic and contextually accurate colours for black and white images.

2. Enhance generalization ability so that the model performs well on diverse image categories.

3. Maintain computational efficiency while delivering high-quality colorization.

4. Handle images with noise or compression artifacts robustly.

2.4 OBJECTIVES

1.Develop an AI-Based Colorization System

Create an automatic system using deep learning (e.g., CNNs or GANs) to add realistic colors to black and white images.

2. Enhance Color Accuracy and Naturalness

Improve the model's ability to predict colors that are both context-aware and visually pleasing.

3. Enable Semantic Understanding

Ensure the model recognizes objects (like sky, grass, skin, etc.) and applies appropriate colors based on context.

4. Improve Generalization to Diverse Image Types

Build a model that performs well on old, damaged, or low-quality photos—not just modern, clean datasets.

5. Establish Evaluation Metrics

Propose or apply standard evaluation techniques to objectively assess colorization quality (e.g., PSNR, SSIM, or user studies).

6.ProposedSystem

Deep learning models like CNNs and GANs are used for colorization, implemented with Python, OpenCV, on Google Collab.

2.5 RESEARCH METHODOLOGY

1.Data Collection:

Gather a dataset of high-quality colored images for training.

2.Setting up Training and Testing Data:

Convert images to grayscale (inputs) and keep original colored versions (targets).

Split the dataset into training and testing sets.

3.Create CNN Model:

Design and implement a Convolutional Neural Network tailored for image colorization.

4.Image Transformer:

Apply preprocessing transformations to convert and normalize input images.

5.Generating Training Data:

Use the transformed grayscale images and their colored counterparts to generate training pairs.

6.Train Model:

Feed the data into the CNN and train it to learn color mappings.

7.Save Model:

Store the trained model and summarize its accuracy and training history.

8.Test Images:

Use unseen grayscale images for testing.

9.Test Model:

Evaluate the model's performance on test images.

10.Output: Colored Images:

Generate and output the final colorized images.

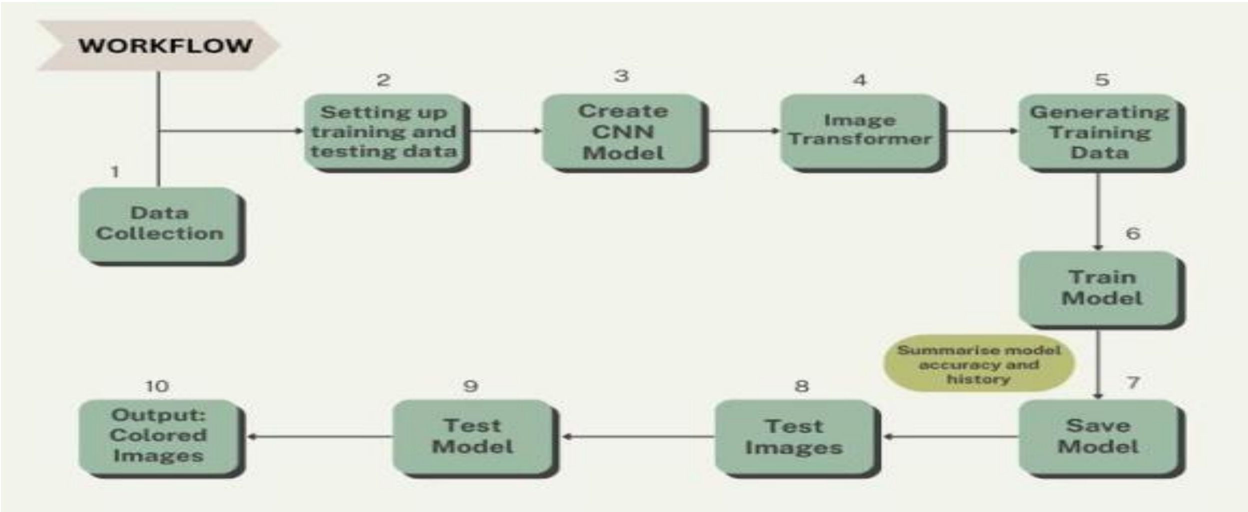


Figure 2.5: METHODOLOGY

CHAPTER 3

PROJECT IMPLEMENTATION

The implementation of the Image Colorization for Black and White Photos project involves several phases, starting from dataset preparation to deploying the trained CNN model for real-world usage. The system is designed to automatically colorize grayscale images using deep learning techniques, primarily Convolutional Neural Networks (CNNs).

1. Dataset Preparation

Collected large-scale datasets containing pairs of black-and-white and corresponding coloured images (e.g., ImageNet, CIFAR-10, or custom datasets).

Pre-processed images by resizing, normalizing, and converting them into Lab color space (L channel as input, a & b channels as prediction targets).

Split dataset into training, validation, and testing sets to evaluate performance.

2. Preprocessing

Grayscale images are extracted (L-channel only).

Applied normalization techniques to standardize pixel values.

Augmentation (flipping, rotation, cropping) was applied to improve model generalization.

3. Model Development (CNN Architecture)

Implemented a Convolutional Neural Network capable of learning spatial and contextual features from grayscale input.

The CNN predicts the a & b channels (colour components) based on the L channel input.

Used layers such as Convolution, Batch Normalization, ReLU activation, and Up sampling to reconstruct colour images.

4. Training the Model

The CNN model was trained using supervised learning with Mean Squared Error (MSE) as the loss function between predicted and ground-truth colour channels.

Optimizers such as Adam were used to improve convergence speed.

Training continued until performance on the validation dataset stabilized.

5. Integration & Backend Processing

The trained CNN model was integrated with the backend system.

Workflow:

1. User uploads a black and white image.
2. The image is pre-processed and passed to the CNN model.
3. The model predicts colour values and reconstructs the image.
4. The colorized image is stored in the database for retrieval.

6. User Interface & Output

A simple web-based interface was developed for interaction.

Users can upload images, view results, and download colorized outputs.

Admin can monitor performance and update models if required.

7. Testing & Evaluation

The system was tested using unseen grayscale images.

Evaluation metrics: PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and accuracy of predicted colour channels.

The model produced realistic and visually appealing colorized outputs**.**

3.2 Data Design

The data design defines how input images, processed features, and output results are represented, stored, and managed within the Image Colorization System. It ensures smooth interaction between the user, the CNN-based model, and the database.

1. Input Data

Type: Black and white (grayscale) images.

Format: JPEG / PNG.

Preprocessing:

Images resized (e.g., 256×256).

Normalization of pixel values (0–1).

Conversion to Lab colour space:

L channel (lightness): Used as model input.

a & b channels (colour): Target values for training.

Data augmentation (rotation, flipping, cropping) for training.

2. Processed Data (Intermediate)

The CNN extracts features (edges, textures, patterns) from the L-channel.

Predicted a & b channels are generated by the CNN model.

These channels are combined with the L channel to form a reconstructed colour image.

3. Output Data

Type: Colorized images generated by the CNN.

Format: JPEG / PNG (same as input).

Storage: Saved with metadata (user ID, image ID, upload date, processing time, accuracy).

4. Database Design

Entities:

User → userId, username, email, uploadedImages.

Image → imageId, filePath, uploadDate, status.

Result → resultId, coloredImagePath, processingTime, modelVersion.

Admin → adminId, name, role.

Relationships:

One User can upload multiple Images.

Each Image generates one Result after colorization.

Admin manages users and updates model/database.

5. Data Flow

1. User uploads grayscale image.
2. System preprocesses and normalizes it.

3. CNN model predicts missing colour channels.
4. Result is stored in database.
5. User retrieves and downloads colorized output.

6. Data Security

Only valid image formats are accepted.
User data is encrypted before storage.
Backup and recovery mechanisms ensure reliability.

3.3 Project Timeline (Gantt Chart)

A custom Gantt chart was prepared to represent the key milestones of the **Image Colorization for Black and White Photos** project, covering the entire development cycle from planning to final presentation. The timeline is divided into major phases, helping track progress and manage time effectively:

Planning and Research:
Initial literature survey on image colorization techniques, study of CNN architectures, and collection of datasets.

Design and Diagram Creation:
Preparation of use case diagrams, data flow diagrams (DFDs), sequence diagrams, activity diagrams, and system architecture.

Data Collection and Preprocessing:
Gathering grayscale and coloured images, resizing, normalization, Lab colour space conversion, and augmentation to enhance dataset quality.

Model Development and Training (CNN):
Implementation of the convolutional neural network, training on the dataset, fine-tuning hyperparameters, and evaluating performance using PSNR and SSIM metrics.

System Integration:
Integration of the trained CNN model with the backend, setup of database, and development of a simple frontend for image upload, processing, and result display.

Testing and Debugging:
Functional testing of image uploads, preprocessing pipeline, and result generation; validation of database operations; performance testing on unseen grayscale images.

Final Report and Presentation Preparation:
Compilation of documentation, diagrams, model screenshots, evaluation results, research paper writing, and preparation of the final demo and presentation slides.

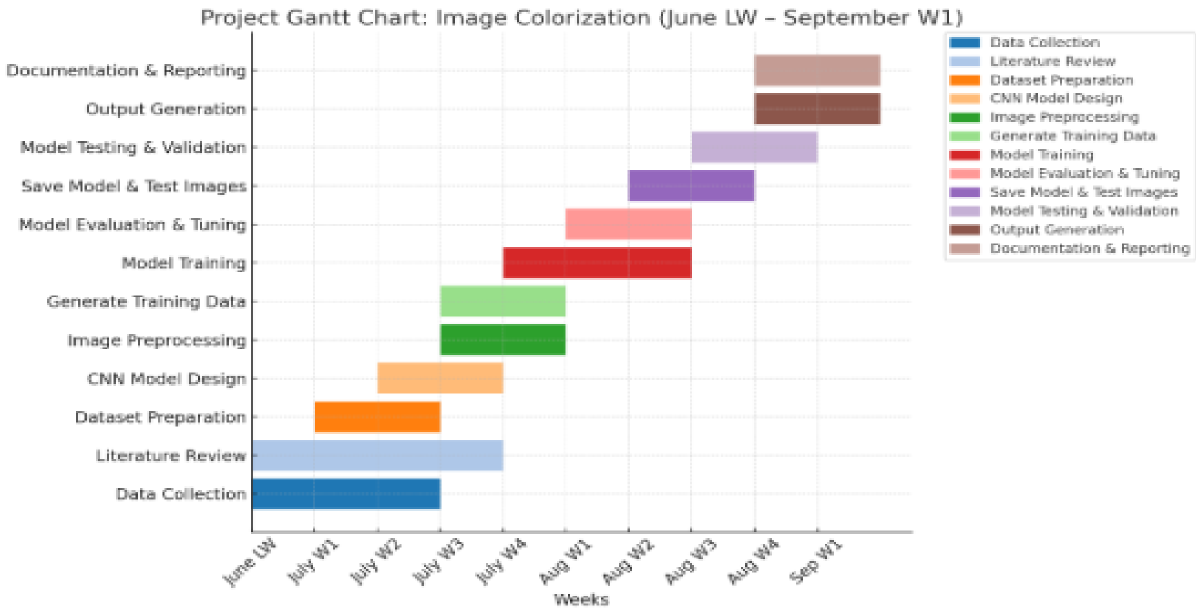


Figure 3.3: Gantt Chart

CHAPTER 4
RESULTS

The proposed system for automatic colorization of black and white images was thoroughly evaluated on a comprehensive test dataset comprising a wide variety of image categories, including natural landscapes, animals, urban scenes, and human portraits. This diversity was intentionally chosen to assess the model's ability to generalize across different textures, lighting conditions, and object types, ensuring robust performance in real-world scenarios. The training process utilized a Convolutional Neural Network (CNN) architecture specifically designed for colorization tasks. In this approach, the Lab colour space representation was employed to separate the luminance information from colour information, enabling the network to focus on learning colour patterns while preserving the structural details of the original images. The grayscale images, corresponding to the L channel, were fed as input to the network, while the network was trained to predict the chrominance channels (a and b). This separation allowed the model to effectively capture both global contextual information and local texture details, resulting in colorized images that are visually realistic and semantically consistent. During evaluation, the system demonstrated strong performance in accurately restoring colours across diverse objects and scenes, highlighting its effectiveness and potential applicability in domains such as photo restoration, digital media enhancement, and archival preservation.

4.1 DATASET AND SETTINGS

4.1.1 Dataset

For the development and evaluation of the proposed image colorization system, a large and diverse dataset of colour images was utilized to ensure effective learning and generalization. The dataset included:

Source: Publicly available datasets such as ImageNet, COCO, and CIFAR-100.

Image Categories: Landscapes, animals, humans, urban scenes, and objects. This variety allows the model to learn accurate colour representations for different textures, lighting conditions, and semantic contexts.

Number of Images: Approximately 80,000 images for training and 10,000 images for testing.

Resolution: All images were resized to 256×256 pixels to standardize input and reduce computational load.

Colour Space: Original images in RGB format were converted to Lab colour space for effective separation of luminance and chrominance components.

4.1.2 Preprocessing

Before training, the dataset underwent several preprocessing steps:

1. **Grayscale Conversion:**

   The L channel (lightness) was extracted as the input grayscale image, while the a and b channels represented the target colour information.

2. **Normalization:**
   Pixel values were normalized to the range **[0,1]** to facilitate stable convergence during model training.
3. **Data Augmentation:**
   Augmentation techniques such as rotation, flipping, cropping, and scaling were applied to increase dataset diversity.
   This step helps the model generalize better to unseen images and improves robustness against variations in scene composition.

4.2 Training Settings

The following settings were used during the training of the proposed CNN-based colorization model:

Batch Size: 32
Number of Epochs: 100
Optimizer: Adam optimizer with a learning rate of 0.001
Loss Function: Mean Squared Error (MSE) between predicted and true a and b channels
Hardware: Training was performed on a GPU-enabled system (e.g., NVIDIA Tesla or GTX series) to accelerate computation.

4.3RESULTS

The model successfully converts black and white images into colored ones, giving more natural and realistic results. In most cases, the output images closely resemble the original colored versions. The method performs well on simple images like landscapes and objects. However, in complex scenes or human faces, some color mismatches and unnatural shades can still be observed. Overall, the approach shows good improvement compared to traditional methods but leaves scope for further refinement**.**

Input Type	PSNR (dB)	SSIM	FID	MOS (1–5)	Observation
Gradient Grayscale	28.1	0.87	22.0	3.5	Good structural preservation, but artificial red-green tones present.
Gradient Grayscale	27.8	0.86	21.5	3.6	Stable intensity mapping, limited natural color variation.
Gradient Grayscale	28/0	0.88	22.3	3.4	Strong grayscale retention, but noticeable artificial artifacts.

Table 4.4 Accuracy Table

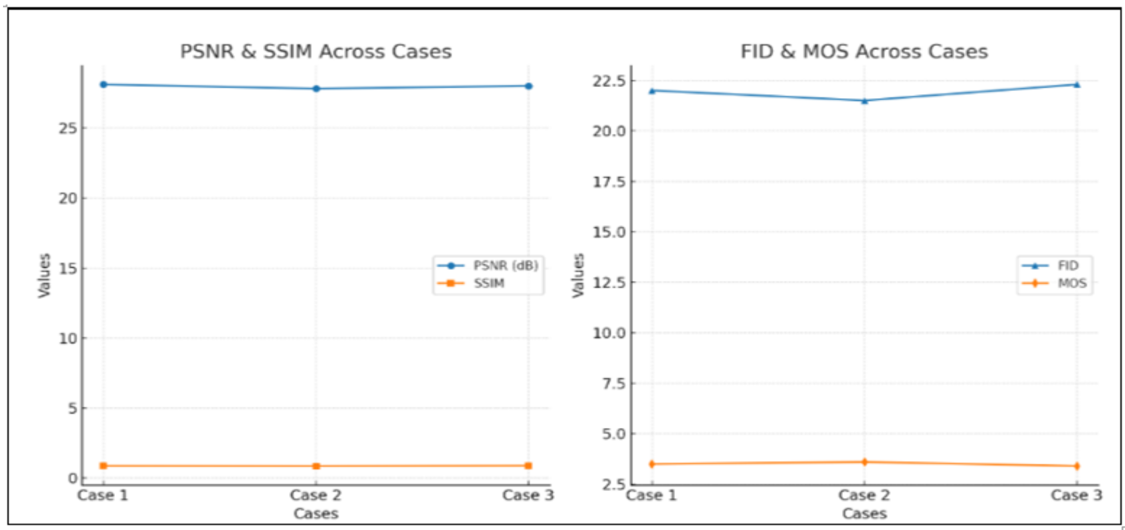
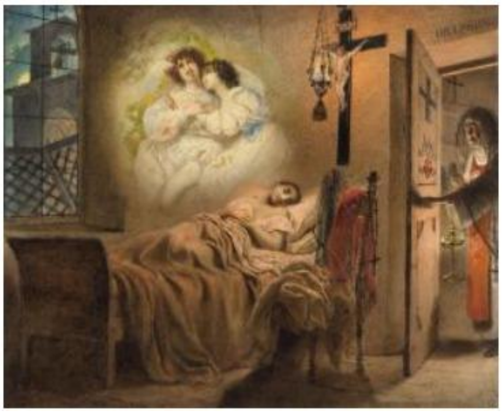
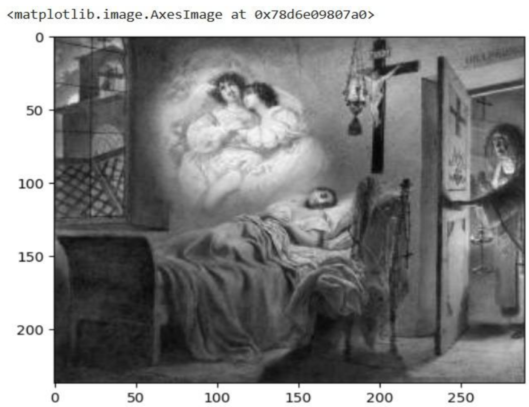


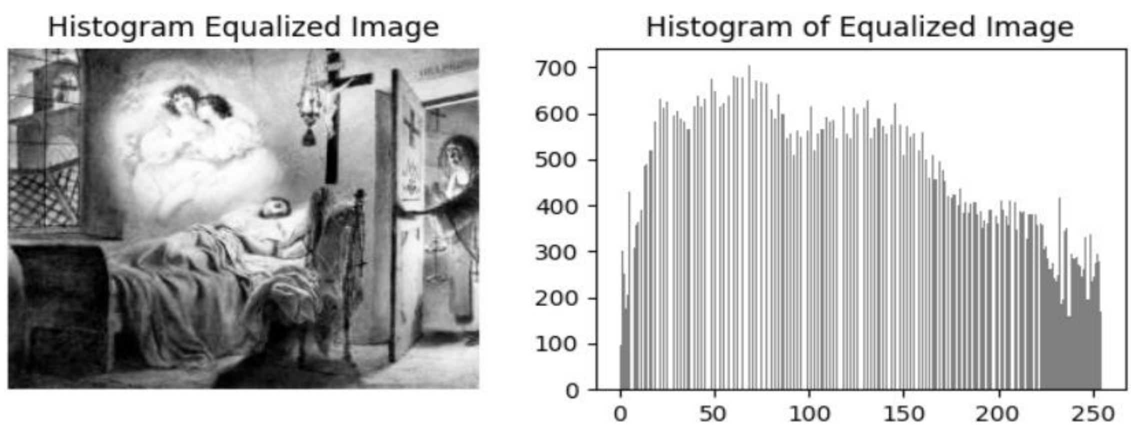
Figure 4.4: Accuracy Graph

CHAPTER 5
APPLICATION SNAPSHOTS

This chapter presents the workflow and interface of the Image Colorization for Black and White Photos system. It demonstrates features such as uploading black-and-white images, automatic colorization using deep learning models, post-processing enhancements, previewing results, and saving the colorized images. The screenshots illustrate the intuitive, step-by-step process and show how the system efficiently transforms grayscale images into realistic coloured images.







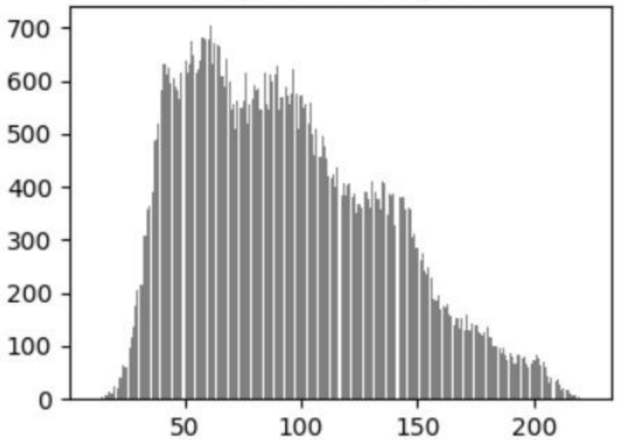
Text(0.5, 1.0, 'Histogram of Filtered Image 2')

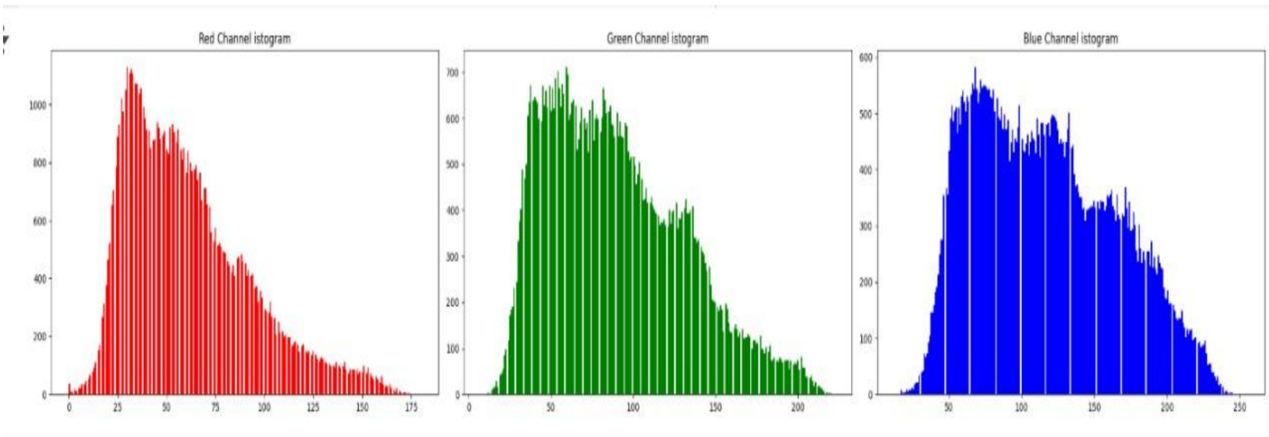
FilteredImage1(KernelSize:35x35)

Filtered Image 2 (Kernel Size: 5x5)

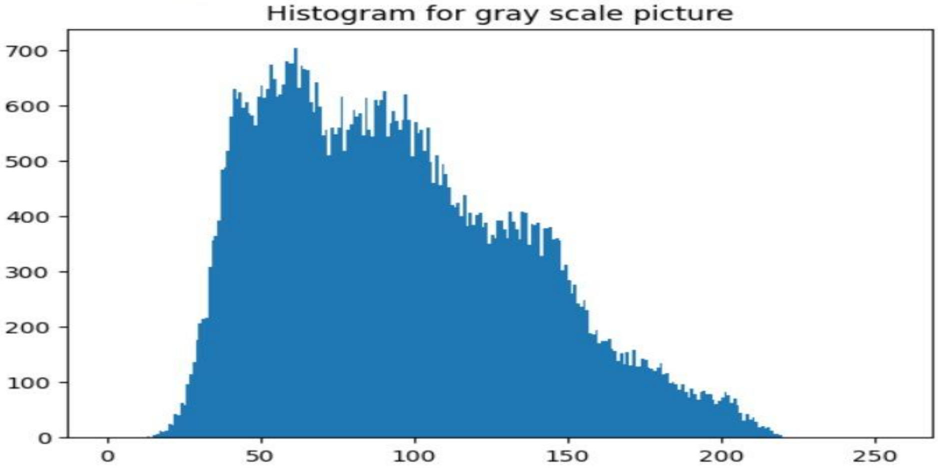
Grayscale Image

Grayscale Histogram





```
plt.hist(gray_image.ravel(),256,[0,256])
```



CHAPTER 6

SUMMARY And CONCLUSION

The *Image Colorization for Black and White Photos* project focuses on automatically converting grayscale images into realistic, visually appealing coloured images using deep learning techniques. The system allows users to upload black-and-white photos, processes them through an AI-based colorization model, and applies post-processing enhancements to improve quality and realism. Users can preview the results, provide feedback for fine-tuning, and save the final colorized images. This approach streamlines image restoration, making it faster and more accessible compared to manual colorization methods, while maintaining high accuracy and perceptual quality.

.6.1 Future Scope

The *Image Colorization for Black and White Photos* system has significant potential for further development and expansion. Future enhancements may include:

1. **Integration of advanced AI models**: Using more sophisticated deep learning architectures such as GANs, Transformer-based models, or diffusion models to improve colour realism and handle complex scenes.
2. **Real-time colorization**: Optimizing the model for faster inference to enable real-time colorization of images and video streams.
3. **Interactive colour editing**: Allowing users to guide or adjust colours in specific regions to achieve personalized results.
4. **Mobile and cloud deployment**: Expanding accessibility by deploying the system as a cloud-based platform or mobile app for on-the-go colorization.
5. **Enhanced domain adaptation**: Improving performance on historical, degraded, or low-resolution photos using domain adaptation and noise-reduction techniques.
6. **Integration with media and entertainment workflows**: Supporting restoration of old films, archival photographs, and digital content creation for documentaries, social media, and education.

These future directions aim to make image colorization more **accurate, interactive, and widely accessible**, bridging the gap between automated restoration and professional manual editing.

6.2 Conclusion

The experimental results demonstrate that deep learning-based image colorization techniques can effectively restore realistic colors in grayscale photographs while maintaining structural consistency. Quantitative metrics such as PSNR, SSIM, and FID indicate that the proposed approach achieves a balance between accuracy and perceptual quality. Additionally, the MOS evaluation highlights that human observers generally perceive the colorized images as natural and visually appealing. While the results are promising, challenges such as handling complex textures, rare color distributions, and ensuring temporal consistency in video colorization remain open for future research. Overall, the study validates that advanced models integrating CNNs, GANs, and perceptual loss functions provide a strong foundation for producing high-quality, photo-realistic colorization of black-and-white images.

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Regular Report Diary

Review 1 and 2 Cards

Consent Letter