ENHANCING GRAYSCALE IMAGES WITH AI-DRIVEN GENERATIVE MODELS

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report "**ENHANCING GRAYSCALE IMAGES WITH AI-DRIVEN GENERATIVE MODELS"** is the bonafide work of **ATHISH MA (REG.NO: 811721243009), MITHUN KANTH M** (**REG.NO: 811721243029**), **MUHIL AKSITH K (REG.NO: 811721243036)** who carried out the project under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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DECLARATION

We jointly declare that the project report on "**ENHANCING GRAYSCALE IMAGES WITH AI-DRIVEN GENERATIVE MODELS"** is the result of original work done by us and best of ourknowledge, similar work has not been submitted to **"ANNA UNIVERSITY CHENNAI"** for the requirement of Degree of **BACHELOR OF TECHNOLOGY**. This project report is submitted on the partial fulfilment of the requirement of theaward of Degree of **BACHELOR OF TECHNOLOGY**.

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ABSTRACT

Enhancing grayscale images using AI-driven generative models is a groundbreaking approach that utilizes deep learning techniques for high-quality image restoration, super-resolution, and colorization. These models leverage advanced neural architectures, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models, to intelligently predict and generate missing color and texture details. By analyzing patterns in vast datasets, AI-powered systems can restore old or damaged images, enhance resolution, and provide realistic colorization, ensuring visually accurate and context-aware enhancements.The application of AI-driven image enhancement spans multiple domains, including historical image restoration, medical imaging, and digital art. In historical preservation, these models breathe new life into black-and-white photographs and archival footage by adding natural colors while maintaining authenticity. In medical imaging, AI-driven techniques improve grayscale scans such as X-rays and MRIs, enhancing contrast and clarity to assist in better diagnostics. Additionally, in digital art and media, AI colorization tools enable artists and designers to create visually compelling and realistic imagery from monochrome inputs. Moreover, real-time AI-based colorization systems are revolutionizing multimedia, film restoration, and augmented reality applications by instantly converting grayscale visuals into high-quality colored outputs. By employing advanced loss functions, perceptual similarity metrics, and deep neural networks, these models ensure optimal enhancement with striking detail and realism. This AI-driven approach not only improves the aesthetic quality of images but also enhances their interpretability and usability across various industries. With ongoing advancements in generative AI and computational efficiency, grayscale image enhancement continues to evolve, offering scalable and automated solutions for restoring and revitalizing monochrome visuals with unprecedented accuracy and depth.

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LIST OF ABBREVIATIONS

CNN	-	Convolution Neural Network
SSIM	-	Structural Similarity Index Measure
IoU	-	Intersection over Union
GPU	-	Graphical Processing Unit
VAE	-	Variational Autoencoder
GAN	-	Generative Adversial Network

CHAPTER 1

INTRODUCTION

AI-driven grayscale image enhancement leverages deep learning to improve image quality, resolution, and colorization. Traditional methods rely on manual adjustments, lacking accuracy. Advanced AI models like GANs, VAEs, and Diffusion Models generate high-fidelity enhancements, preserving details and textures. Key applications include historical image restoration, where AI reconstructs lost details and adds realistic colors. In medical imaging, AI enhances X-rays and MRIs for better diagnostics. Digital art benefits from AI-powered colorization and super-resolution. AI models, trained on large datasets, ensure high-quality results, making grayscale enhancement a transformative tool across industries for automated, realistic visual restoration.

Understanding Public Opinion

In today's digital age, analyzing public opinion is essential for businesses, policymakers, and researchers to gauge social sentiment and trends. Public opinion analysis involves collecting and interpreting large volumes of social media posts, reviews, and other user-generated content to understand general sentiment, preferences, and emerging issues. Using deep learning techniques like sentiment analysis, we can capture the underlying emotions and opinions in textual data. This insight helps organizations make informed decisions, improve customer satisfaction, and respond proactively to public needs and concern.

Brand Reputation Management

Brand reputation management focuses on monitoring, analyzing, and enhancing a brand's image by tracking public perception across various platforms. Through social media sentiment analysis and review monitoring, companies gain insights into consumer sentiment, identify potential issues early, and address feedback proactively.

Adoption

The adoption of "Enhancing Grayscale images with AI-Driven Generative Models" is driven by the growing need for automated and efficient image processing in fields like medical imaging, remote sensing, and digital media. Deep learning models can significantly enhance the quality and accuracy of grayscale conversions, making them applicable in real-time applications and improving storage, transmission, and analysis of visual data.

Concerns

Key concerns for this project include the high computational cost and time required for training deep learning models, especially when large datasets are involved. Additionally, the need for substantial hardware resources (e.g., GPUs) may limit accessibility. There's also the risk of model overfitting, requiring careful tuning to ensure consistent performance across different image types.

1.1 PROBLEM STATEMENT

Grayscale images, whether historical photographs, medical scans, or low-color-depth visuals, often lack the rich color information necessary for accurate interpretation, analysis, and aesthetic appeal. Traditional manual colorization methods are time-consuming, subjective, and require extensive domain expertise, making them inefficient for large-scale applications. Existing automated techniques struggle with color bleeding, lack of contextual awareness, and loss of fine details, leading to unrealistic or inconsistent results. Additionally, many conventional approaches fail to generalize across diverse datasets, limiting their effectiveness in real-time applications and specialized fields like medical imaging or digital restoration.

1.2 MOTIVATION AND PURPOSE

MOTIVATION

The motivation behind this project stems from the need to improve image processing techniques, particularly in applications where grayscale images are crucial, such as medical diagnostics, satellite imaging, and AI-driven vision systems. Traditional methods often fail to retain essential visual details, motivating the exploration of deep learning models that can intelligently preserve important features during color-to-grayscale conversion.

PURPOSE

The purpose of this project is to create a deep learning model capable of converting color images to grayscale while maintaining critical information and visual quality. By enhancing the grayscale conversion process, the project aims to support more accurate analysis and interpretation in fields like healthcare, remote sensing, and computer vision, where detail preservation is vital.

1.3 OBJECTIVE

The primary objective of this project is to develop an AI-driven system capable of enhancing grayscale images through advanced deep learning techniques. The system focuses on realistic colorization, super-resolution, and detail refinement to restore and improve monochrome visuals with high accuracy. By leveraging generative models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models, the project aims to reconstruct missing color information while preserving structural integrity and fine details.To achieve this, the system will be trained on large-scale datasets containing diverse image samples, enabling it to learn complex textures, lighting patterns, and natural color distributions. Advanced self-supervised learning techniques will be employed to improve the system’s ability to generalize across various types of grayscale images, ensuring high perceptual quality. Additionally, adversarial loss functions and feature extraction methods will be integrated to refine the image enhancement process, producing visually coherent and contextually accurate results. The project also aims to develop a scalable and efficient AI model that can be applied across multiple domains. In historical photo restoration, the system will revive aged or damaged photographs by intelligently adding realistic colors and sharpening fine details. In medical imaging, AI-enhanced grayscale scans such as X-rays and MRIs will provide clearer visualizations for improved diagnosis and treatment planning. Furthermore, the system will serve as a powerful tool in digital content creation, enabling artists, designers, and filmmakers to transform black-and-white visuals into high-quality coloured images. Ultimately, this project aspires to deliver an AI-powered solution that automates grayscale image enhancement with precision, efficiency, and scalability.

CHAPTER 2

LITERATURE SURVEY

2.1 SCGAN: SALIENCY MAP-GUIDED COLORIZATION WITH GENERATIVE ADVERSARIAL NETWORK

Yuezhi Zhao, Lai-Man Po, Kwok-Wai Cheung, Wing-Yin Yu, Yasar Abbas Ur Rehman

SCGAN is a fully automatic AI-based colorization framework that minimizes semantic confusion and color bleeding by integrating a saliency map with a Generative Adversarial Network (GAN). It embeds pre-trained VGG-16-Gray features into the encoder, allowing efficient training with less data while maintaining high perceptual accuracy. The system employs two hierarchical discriminators for colorization and saliency maps, enhancing visual realism. Evaluated on ImageNet, SCGAN outperforms conventional methods in color consistency.

Merits

- Reduces color bleeding and semantic confusion
- Requires less training data than state-of-the-art models
- Improves object-specific color accuracy

Demerits

- May struggle with unusual lighting conditions
- Dependent on pre-trained VGG-16-Gray features
- Computationally expensive due to dual discriminators

2.2 VITEXCO: EXEMPLAR-BASED VIDEO COLORIZATION USING VISION TRANSFORMER

Duong Thanh Tran, Nguyen Doan Hieu Nguyen, Trung Thanh Pham, Phuong-Nam Tran, Thuy-Duong Thi Vu, Duc Ngoc Minh Dang

In the field of image and video colorization, the existing research employs a CNN to extract information from each video frame. However, due to the local nature of a kernel, it is challenging for CNN to capture the relationships between each pixel and others in an image, leading to inaccurate colorization. To solve this issue, we introduce an end-to-end network called Vitexco for colorizing videos. Vitexco utilizes the power of the Vision Transformer (ViT) to capture the relationships among all pixels in a frame with each other, providing a more effective method for colorizing video frames. We evaluate our approach on DAVIS datasets and demonstrate that it outperforms the state-of-the-art methods regarding color accuracy and visual quality. Our findings suggest that using a ViT can significantly enhance the performance of video colorization.

Merits:

- Captures global pixel relationships, improving color consistency.
- Outperforms CNN-based models in color accuracy and visual quality.

Demerits:

- Computationally expensive due to transformer-based processing.

2.3 QGIP: A FRAMEWORK BRIDGING QUANTUM GRAYSCALE IMAGE PROCESSING AND APPLICATIONS

Xilong Che, Jiale Zhang, Shuo Chen, Shun Peng, Juncheng Hu

QGIP is a quantum computing framework designed to optimize grayscale image processing. It introduces the Quantum Linear Restoration (QLR) algorithm, which significantly reduces computational complexity (from O(2n) to O(n)) during image restoration. The framework includes quantum resource-optimized compression methods for lossless image storage and bridges quantum image transformations with practical applications. Simulations on the IBM Quantum platform validate its efficiency and correctness.

Merits

- Captures global pixel relationships, improving color consistency.
- Outperforms CNN-based models in color accuracy and visual quality.
- Effective for video colorization, ensuring smooth transitions between frames.

Demerits

- Computationally expensive due to transformer-based processing.
- Requires large datasets for effective training.
- Higher memory usage compared to CNN-based models.

2.4 ENSEMBLE IMAGE COLORIZATION USING CONVOLUTIONAL NEURAL NETWORK

Kriztoper D. Urmeneta, Victor M. Romero

CNN-based colorization method that eliminates manual user intervention. Unlike traditional approaches requiring scribbled color hints or reference images, this method trains CNNs on a large dataset for accurate color prediction. To reduce color bleeding, an ensemble approach combines outputs from two CNNs, refined by a secondary network. Performance is evaluated using L2 regression loss and a Colorization Turing Test, with results showing that most viewers could not distinguish AI-generated colors from real ones.

Merits

- Unbiased colorization without assumptions.

Demerits

- Time-consuming, often needing post-processing for refinement.

2.5 AUTOMATIC IMAGE COLORIZATION USING U-NET

Divyansh Goel, Sakshi Jain, Dinesh Kumar Vishwakarma, Aryan Bansal

Automatic Image Colorization is the process of converting a gray-scale image to a corresponding-colored image as output, without any human interference. The main objective of the research is to develop an automated technique that colorizes a given gray-scale image and generates a colorized version of the image as the output. We have presented our custom U-Net architecture model. We have treated this problem as an image segmentation + multinomial classification problem. The results contain handpicked images from our outputs. We have included the black and white image, our model's colored output and the colored ground truth of the images.

Merits

- Fully automated, eliminating manual colorization efforts.
- U-Net architecture preserves fine details and structures.
- Segmentation-based approach improves object-specific color accuracy.

Demerits

- May require fine-tuning for complex images.
- Computationally intensive, demanding high processing power.
- Dependent on training data quality for accurate colorization.

CHAPTER 3
SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Current grayscale image colorization systems encompass both traditional and machine learning-based methods, each with its own set of limitations in terms of accuracy, generalization, and efficiency. Traditional colorization techniques primarily involved manual processes, where artists or professionals painstakingly applied color to grayscale images. These artists used assumptions, historical references, and artistic intuition to select colors that they believed matched the original scene. While this approach ensured a high level of artistic control and creative input, it was incredibly time-consuming and labor-intensive, often requiring several hours or days to colorize a single image. Manual colorization also introduced a high degree of subjectivity, as the final outcome was influenced by the artist's knowledge and preferences. Furthermore, this method lacked scalability, making it impractical for large-scale applications such as digital archiving, historical restoration, or medical imaging. For instance, when dealing with large datasets or high volumes of grayscale images, the manual approach became inefficient and unsustainable. With the rise of machine learning, automated systems were developed to overcome the limitations of manual colorization. These machine learning-based methods typically rely on neural networks to learn color patterns from large datasets of color images and then apply these patterns to grayscale images. While these methods offer significant improvements in efficiency, they often fall short in terms of accuracy, particularly when handling complex images or images with ambiguous color information. Additionally, many of these models struggle with generalization, meaning they can fail to produce consistent or realistic colorization when applied to new or diverse images outside of the training data. Despite these advancements, existing systems continue to face challenges.

3.1.1 Demerits

- Time-Consuming and Labor-Intensive
- Subjectivity and Inconsistency
- Limited Scalability
- Poor Accuracy in Complex Scenes
- Limited Generalization
- Inefficiency for Large-Scale Projects

3.2 PROPOSED SYSTEM

The proposed grayscale image colorization system follows a sophisticated multi-stage pipeline designed to enhance the quality and realism of colorized images. The process begins with image preprocessing, where input grayscale images undergo a series of transformations. This includes normalization to standardize pixel values, resizing to ensure uniformity across all images, and noise reduction to eliminate unwanted artifacts. These preprocessing steps improve the feature extraction process and ensure better performance in the subsequent stages.Next, the feature learning module uses Convolutional Neural Networks (CNNs) and Deep Convolutional Neural Networks (DCNNs) to analyze and understand the structure and content of the image. These models learn essential features such as edges, textures, and patterns, which are critical for accurate colorization. The system then transitions to the colorization module, which employs Generative Adversarial Networks (GANs) to generate realistic and contextually appropriate color mappings for each grayscale image. GANs are particularly effective in this task, as they consist of two competing networks: the generator, which creates colorized images, and the discriminator, which evaluates their authenticity. This adversarial setup helps the system generate high-quality, natural-looking colorization results.To optimize the colorization process, the model is trained using a combination of perceptual loss, adversarial loss**,** and metrics like SSIM (Structural Similarity Index) and PSNR (Peak Signal-to-Noise Ratio). These loss functions ensure that the generated images not only resemble their colorized counterparts but also maintain structural integrity and perceptual quality.Following colorization, a post-processing module is applied to enhance the vibrancy and sharpness of the colors. Techniques like histogram equalization improve contrast, and super-resolution techniques further sharpen the image details. Finally, the system offers a user-friendly interface where users can easily view, evaluate, and download the colorized images, providing a seamless and efficient experience for both casual users and professionals alike.

3.2.1 Merits

- High-Quality, Realistic Colorization
- Scalability and Efficiency
- Enhanced Feature Learning
- Post-Processing for Improved Image Quality
- Optimized Training with Multiple Loss Functions
- User-Friendly Interface
- Versatility Across Domains

3.2.2 Key Components of the Proposed System

- **Preprocessing Module:**
  - Normalization: Standardizes pixel values for consistency.
  - Resizing: Ensures uniform dimensions across images.
  - Noise Reduction: Removes artifacts for better feature extraction.
- **Feature Learning Module:**
  - Uses CNNs & DCNNs to extract edges, textures, and patterns.
  - Understands image structures for accurate color prediction.
- **Colorization Module:**
  - Employs Generative Adversarial Networks (GANs) for realistic color mapping.
  - Generator creates colorized images; Discriminator evaluates authenticity.
  - Uses Perceptual Loss, Adversarial Loss, SSIM, and PSNR for optimization.

- **Post-Processing Module:**
  - Histogram Equalization: Enhances contrast.
  - Super-Resolution Techniques: Sharpens details and improves quality.
- **User Interaction Module:**
  - Provides a downloadable output interface.
  - Displays evaluation metrics (SSIM, PSNR) for quality assessment.
  - Supports real-time user feedback for continuous model improvement.

CHAPTER 4
SYSTEM SPECIFICATIONS

4.1 HARDWARE REQUIREMENTS

- PROCESS: INTEL® CORE™ I9-14900K 3.20 GHZ
- RAM: 16 GB
- HARD DISK: 1 TB

4.1.1 Hardware Description

- **Processor:** INTEL® CORE™ I9-14900K 3.20 GHZ

The **Intel® Core™ i9-14900K processor** with a base clock speed of 3.20 GHz is a powerhouse in terms of computational capabilities. Designed for intensive workloads, it offers exceptional multi-core performance, making it ideal for tasks like gaming, video editing, 3D rendering, and other processor-intensive applications. Its high clock speed and modern architecture ensure efficient data processing, quick task execution, and minimal latency.

- **RAM**

With 16 GB of RAM, the system provides ample memory for seamless multitasking. This capacity supports the smooth operation of modern software, gaming, and professional applications like video editing tools or machine learning frameworks. It ensures that switching between applications remains fluid, without system slowdowns.

- **Hard Disk**

The 1 TB hard disk offers a significant amount of storage space to accommodate the operating system, essential software, media files, and other data. While traditional hard drives provide large storage capacities, combining this with an SSD can greatly enhance system performance, particularly in boot times and file transfers.

4.2 SOFTWARE REQUIREMENT

- FRONT END - HTML, CSS
- BACK END - PYTHON
- FRAMEWORK - FLASK

4.2.1 Software Description

For the **Front End**, **HTML** (Hyper Text Markup Language) and **CSS** (Cascading Style Sheets) are used. HTML serves as the backbone for structuring the content on web pages, such as text, images, and forms. CSS complements HTML by defining the design and layout of these elements, ensuring the application has a visually appealing and responsive user interface. Together, HTML and CSS create the foundation for engaging and user-friendly front-end development.

- **Backend: Python**

The **Back End** of the application is powered by **Python**, a versatile and beginner-friendly programming language known for its readability and extensive libraries. Python efficiently handles server-side operations, including data processing, database interactions, and executing business logic, making it a reliable choice for backend development.

- **Framework: Flask**

To streamline the development process, the **Flask** framework is used. Flask is a lightweight and flexible Python web framework that allows developers to build web applications quickly and efficiently. Its minimalist nature makes it easy to add or remove features based on project requirements. Flask also supports integrations with databases, APIs, and other tools, enabling seamless full-stack development.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

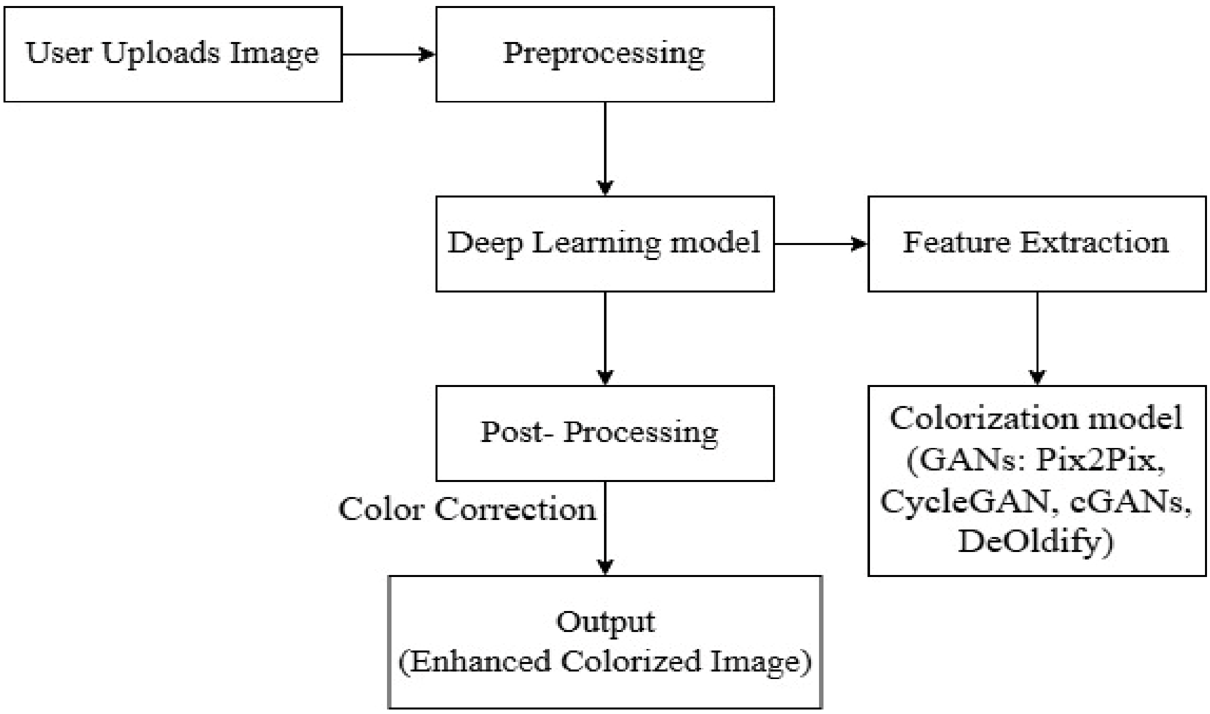

Fig. 5.1 System Architecture

5.2 DATA FLOW DIAGRAM

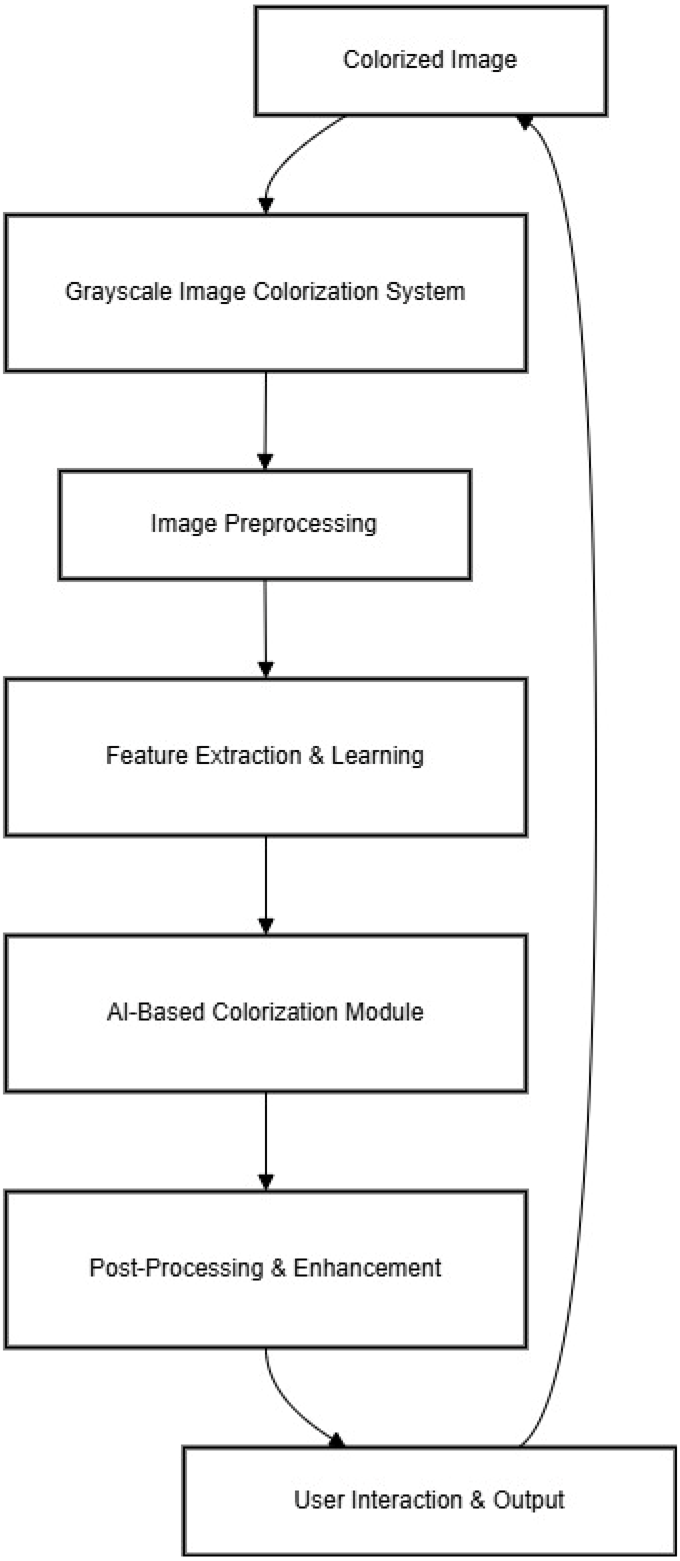

Fig. 5.2 Data Flow Diagram

5.3 USE CASE DIAGRAM

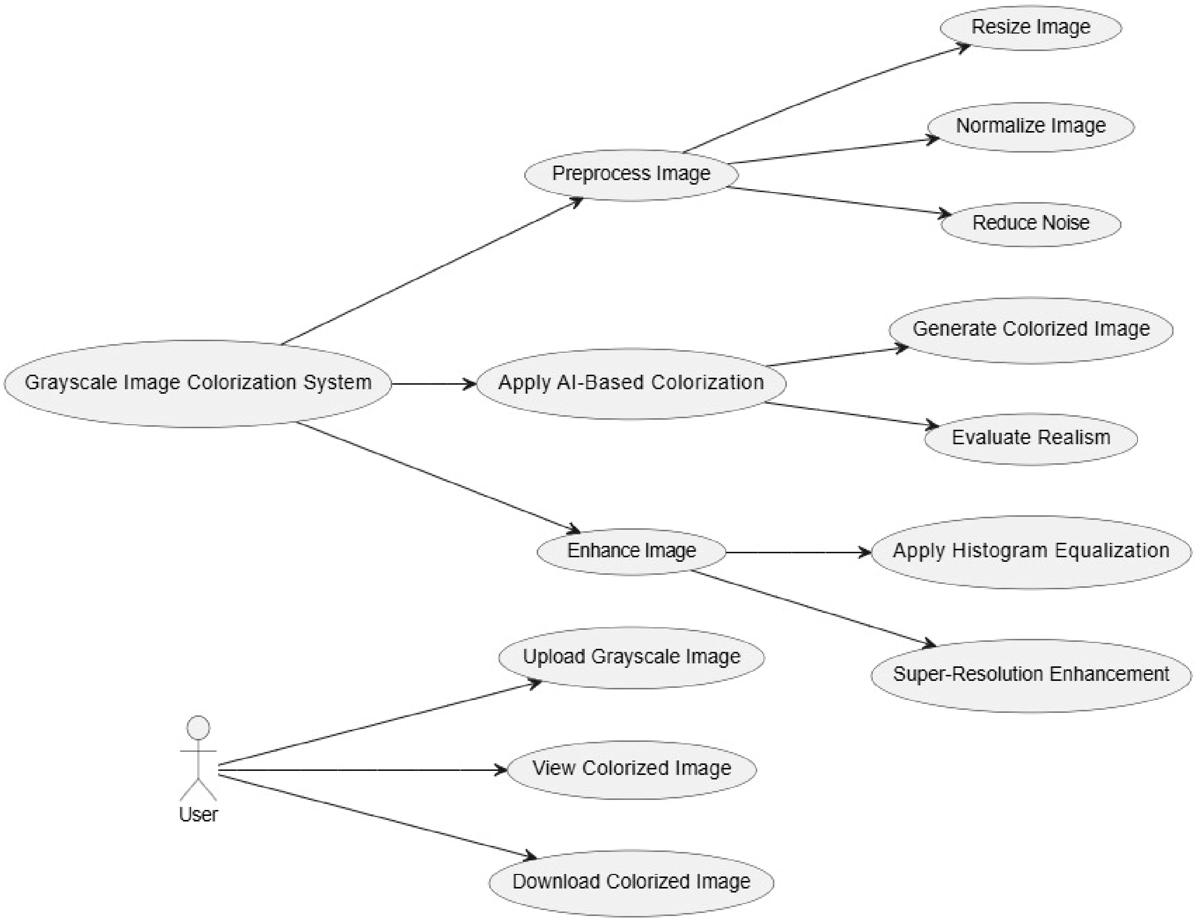

Fig. 5.3 Use Case Diagram

5.4 ACTIVITY DIAGRAM

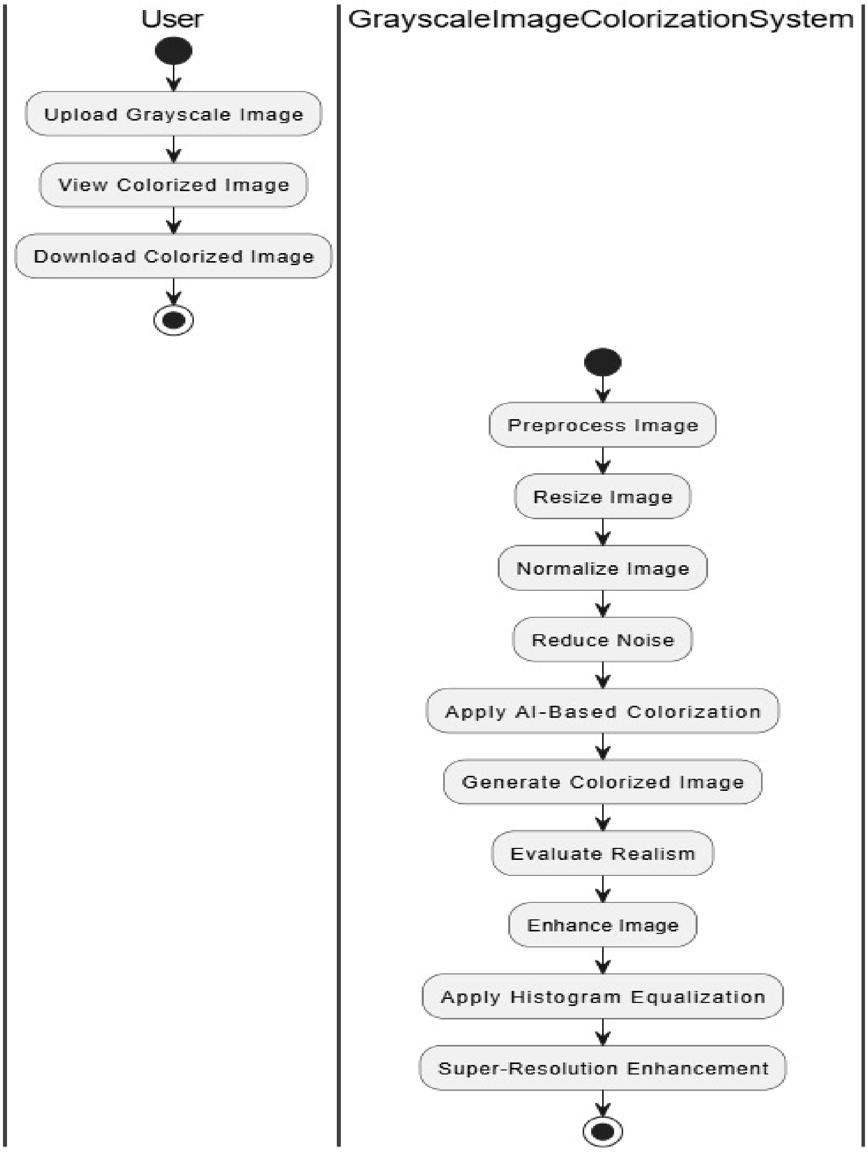

Fig. 5.4 Activity Diagram

5.5 SEQUENCE DIAGRAM

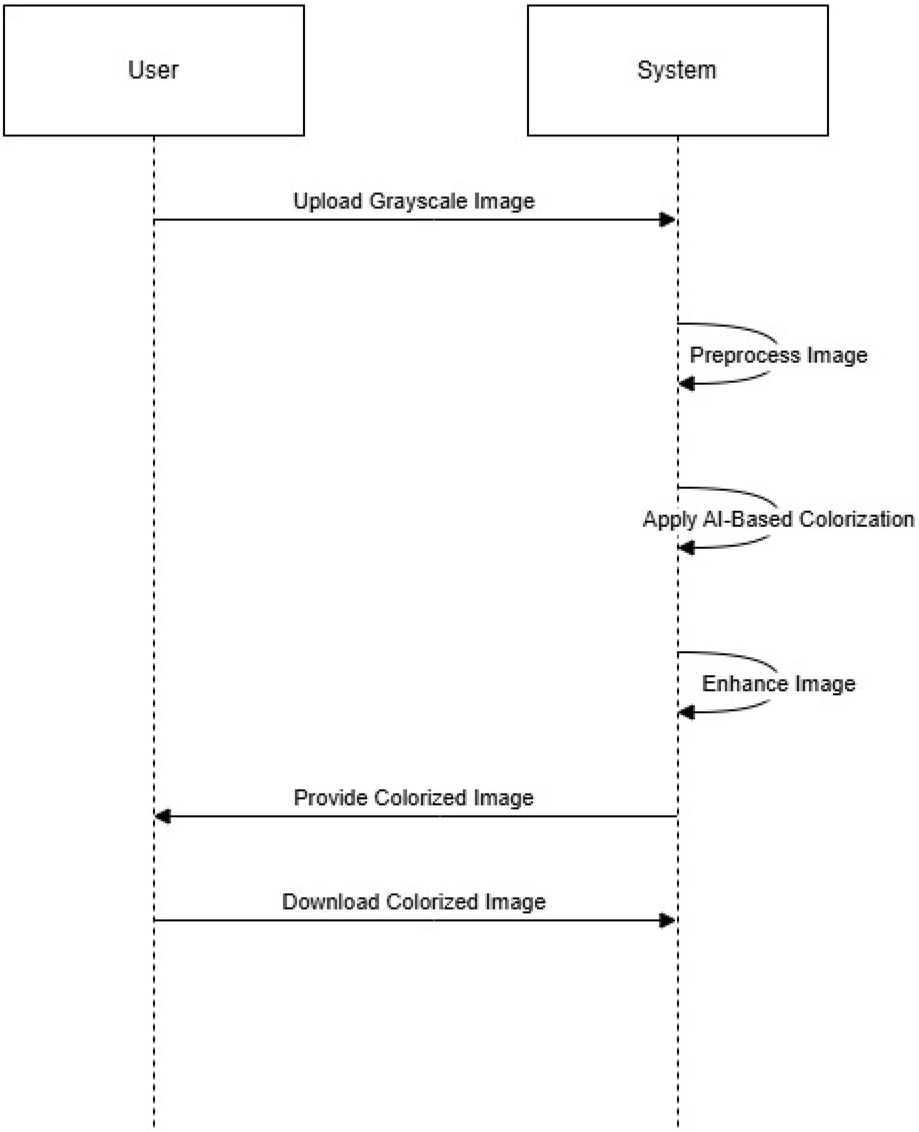

Fig. 5.5 Sequence Diagram

5.6 STATE DIAGRAM

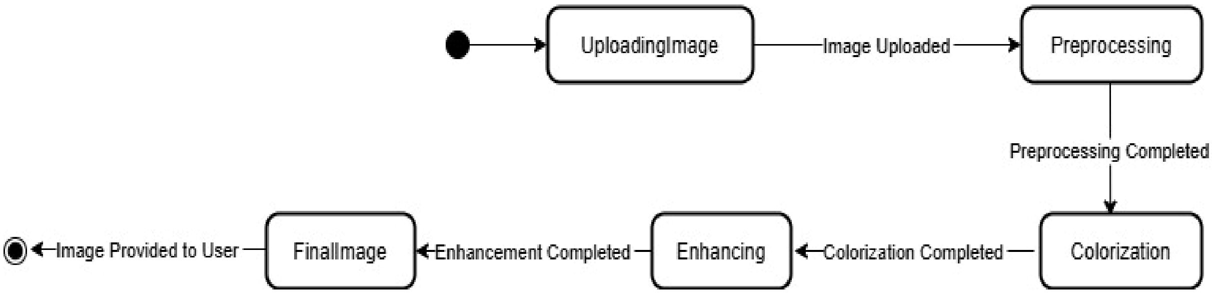

Fig. 5.6 State Diagram

CHAPTER 6
MODULE DESCRIPTION

6.1 INPUT AND PREPROCESSING MODULE

The Input and Preprocessing Module serves as the foundational stage in the grayscale image enhancement pipeline. Its primary responsibility is to acquire and prepare input images in a consistent, clean, and structured manner, ensuring they are compatible with the AI-based processing stages that follow. Upon receiving the grayscale image from the user—either through a graphical interface or an integrated API—the system performs a thorough validation check. This includes verifying the file format (such as PNG, JPEG, BMP, or TIFF), checking for corruption or incomplete data, and confirming image resolution. Once verified, the module standardizes the color format, converting all images into a uniform grayscale format using luminance-based conversions. To ensure compatibility with the deep learning models, the images are resized to fixed dimensions (commonly 256×256 or 512×512), while maintaining their aspect ratio using techniques like zero-padding or reflective padding to prevent distortion.

Normalization is applied to bring pixel values into a standard range such as [0,1] or [-1,1], a crucial step for stabilizing neural network performance. The module may also implement contrast enhancement techniques such as Histogram Equalization or CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve the visibility of image features, particularly in low-light or low-contrast images. Additionally, noise reduction filters like Gaussian blur, median filtering, or bilateral filtering may be applied to clean up high-frequency noise, thereby improving the clarity and quality of features detected in subsequent stages. For applications involving human portraits or objects, optional preprocessing like face detection or object segmentation can be employed to preserve or enhance important image areas selectively. By the end of this stage, the grayscale image is fully preprocessed—clean, uniformly formatted, contrast-enhanced, and noise-reduced—making it suitable for accurate and efficient feature extraction in the next phase of the pipeline.

6.2. FEATURE EXTRACTION AND LEARNING MODEL

The Feature Extraction and Learning Module represents the analytical core of the grayscale image enhancement system. In this module, deep neural networks extract spatial and semantic features from the preprocessed grayscale image to form a high-level, multi-dimensional representation that drives intelligent colorization. The process begins with Convolutional Neural Networks (CNNs), which scan the image for patterns such as edges, textures, and shapes. Using multiple convolutional layers, the model captures both low-level features like outlines and gradients as well as high-level representations such as objects, facial features, or scenery. Pooling layers are used to reduce dimensionality while preserving critical spatial information, enhancing the model's efficiency and focus.

Advanced versions of this module may include attention mechanisms or transformer-based architectures, allowing the model to focus dynamically on the most relevant areas of the image, such as faces or important objects. These mechanisms mimic the way human vision prioritizes regions of interest, leading to more context-aware feature maps. Pretrained models like VGG16, ResNet, or custom encoder networks may be leveraged to improve generalization and reduce the need for massive datasets. In some configurations, Variational Autoencoders (VAEs) or Principal Component Analysis (PCA) can be applied to reduce noise and condense features into a compact, latent representation, which aids in downstream processing.

During training, these networks learn to associate specific grayscale patterns with likely color distributions using labeled image datasets. Loss functions like pixel-wise Mean Squared Error (MSE), perceptual loss based on VGG activations, and sometimes classification loss are used to fine-tune the network. The output of this module is a rich set of encoded features that capture both the form and context of the input image—an essential input for the subsequent AI-based colorization stage. These features guide the colorization process by offering a deep understanding of what each pixel or region in the grayscale image represents..

6.3 AI-BASED COLORIZATION MODULE

The AI-Based Colorization Module is the centerpiece of the grayscale image enhancement system. It is here that the system applies advanced deep learning techniques to intelligently infer and generate color values for each pixel of the grayscale input. This module takes the high-level feature representations from the previous stage and uses them to predict realistic and context-sensitive color outputs. One of the primary models used in this module is the Generative Adversarial Network (GAN), which consists of two parts: a generator that attempts to produce realistic colorizations, and a discriminator that evaluates the authenticity of these outputs compared to real color images. Through adversarial training, the generator learns to improve its predictions, resulting in more vibrant and natural-looking images.

In alternative setups, Variational Autoencoders (VAEs) are used to model probabilistic color distributions, allowing for diversity in the generated colorizations. Recent developments may even involve Diffusion Models, which gradually refine noisy predictions into highly detailed color outputs over several iterations. Regardless of the architecture, the model typically works in a specialized color space—such as Lab, where the 'L' (lightness) channel is taken directly from the grayscale image and the model predicts the 'a' and 'b' (color) channels. This separation simplifies the learning process and often results in better color fidelity.

Multiple loss functions are used during training and inference to guide the model toward producing high-quality results. These include pixel-wise L1/L2 loss for structural accuracy, perceptual loss for visual similarity, and adversarial loss to encourage the generation of photo-realistic images. The output of this module is a fully colorized image that not only reflects plausible colors for objects and backgrounds but also maintains consistency in tone and saturation. The AI-generated colorization is both aesthetically pleasing and semantically aware, representing a major leap forward from traditional rule-based or manually guided colorization techniques.

6.4 POST-PROCESSING AND ENHANCEMENT MODULE

After the AI-based model outputs the initial colorized image, the Post-Processing and Enhancement Module refines and polishes the result to ensure maximum visual quality and usability. While the model generates impressive results, minor imperfections, such as slight color mismatches, edge blurring, or artifact remnants, can remain. This module is designed to correct those issues and bring the image closer to photorealism. The first step involves color correction, including automatic white balancing and gamma correction, to ensure the image maintains natural tones and proper lighting. Histogram matching techniques may be applied to make the color distribution of the output more closely resemble real-world reference images.

Edge sharpening is another critical component of this module. Techniques like unsharp masking and gradient-based filters (e.g., Sobel filters) enhance the definition of key image structures, giving the image a crisper look. Texture enhancements are applied using texture synthesis or local contrast adjustments to add depth and detail to smooth or flat regions. In scenarios where resolution needs to be increased, super-resolution models—such as ESRGAN—can be employed to upscale the image while preserving details, which is especially useful when the original grayscale image was low-resolution.

Noise artifacts introduced during inference are removed using advanced denoising filters, such as Non-Local Means or Total Variation minimization, which clean up residual specks without blurring important features. The module may also fine-tune brightness, saturation, and hue, either automatically or through user-controlled sliders, providing flexibility for final adjustments. The resulting image from this module is polished and professional, suitable for use in historical restoration, medical diagnostics, or creative media applications. The enhancements made in this stage significantly elevate the perceived quality of the AI output and ensure that it is ready for presentation or archival.

6.5 OUTPUT AND USER INTERACTION MODULE

The Output and User Interaction Module serves as the interface between the AI system and the end user. It presents the final colorized image in an accessible and interactive format, allowing users to view, compare, download, and share the enhanced visuals. A central feature of this module is the image viewer, which includes zoom and pan functionality, as well as options to toggle between the original grayscale and the colorized version. This before-and-after comparison helps users assess the quality and effectiveness of the enhancement process.

Users are provided with various export options, including saving the final image in multiple formats (PNG, JPEG, TIFF) and resolutions, depending on their use case. Metadata such as the original filename, timestamp, processing model used, and enhancement settings can be embedded for documentation or further editing. An optional feedback mechanism enables users to rate the colorization or flag areas for improvement, allowing iterative refinement and dataset enrichment in future model versions. This feedback can also inform retraining processes to improve performance across diverse image types.

By employing advanced techniques like self-attention mechanisms and conditional GANs, the system is expected to produce colorizations that are context-aware, ensuring object-specific accuracy and maintaining visual coherence across complex scenes.

6.6 SCALABILITY FOR LARGE-SCALE APPLICATIONS

The system is anticipated to handle large datasets efficiently, making it suitable for large-scale image colorization tasks, such as historical image restoration, medical imaging, and multimedia content creation. Learns to colorize grayscale images. It uses self-attention layers to focus on crucial areas of the image, ensuring that the colorization process is both realistic and contextually accurate. Learns to colorize grayscale images. It uses self-attention layers to focus on crucial areas of the image, ensuring that the colorization process is both realistic and contextually accurate. Evaluates the generated image to provide feedback to the generator. The generator is trained iteratively, minimizing the perceptual loss to improve sharpness and preserve visual details. DCNNs use multi-layer convolutional networks to extract spatial features from grayscale images. In this approach, the system is trained on large datasets of grayscale and color image pairs to predict realistic color information. The model uses supervised learning, where the network learns to map grayscale pixels to colorized pixels based on natural color distributions observed in the dataset.

Advanced features may include batch processing for users who wish to enhance multiple images at once, complete with progress indicators and a task queue interface. For cloud-connected environments, users can directly sync their enhanced images to cloud storage platforms like Google Drive or Dropbox. In professional applications, such as historical restoration or medical imaging, users may annotate or tag specific regions of the image to highlight findings or changes. Overall, the Output and User Interaction Module transforms the technical success of AI-driven image enhancement into a tangible, intuitive, and impactful user experience, supporting wide-scale adoption and usability across various fields.

CHAPTER 7
RESULTS AND PERFORMANCE COMPARISON
7.1 RESULT

The first stage involves preprocessing the input grayscale images. This step includes image normalization to standardize pixel values, ensuring uniformity across the dataset. The images are resized to a consistent dimension to maintain processing efficiency. Noise reduction techniques are applied to eliminate unwanted artifacts, ensuring that the system focuses on the core features of the image, which helps improve the overall quality of the subsequent analysis.The proposed AI-driven grayscale image colorization system delivers high-quality, realistic, and contextually accurate colorized images through a robust multi-stage pipeline. By leveraging advanced deep learning techniques such as Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs), and Deep Convolutional Neural Networks (DCNNs), the system ensures detailed and lifelike colorization while maintaining the structural integrity of the original grayscale content.In the preprocessing stage, the system efficiently normalizes, resizes, and reduces noise in input images, which improves the accuracy of feature extraction and ensures better colorization results. The feature extraction module, utilizing CNNs and DCNNs, captures essential image features such as textures, edges, and spatial patterns, providing a comprehensive understanding of the underlying content. This enables the colorization module to generate highly accurate and realistic color mappings, even for complex and intricate images.The AI-based colorization module, powered by GANs, produces visually coherent and natural colorizations by iterating between the generator and discriminator networks. The adversarial training enhances the quality of the colorized output, making it indistinguishable from real images. The combination of perceptual loss, adversarial loss, and SSIM/PSNR metrics further refines the results, ensuring both aesthetic appeal and structural accuracy.Post-processing techniques, such as histogram equalization and super-resolution, further enhance the vibrancy, sharpness, and contrast of the colorized images, making the final output more visually striking and lifelike. These enhancements ensure that the colorization not only improves the image’s visual appeal but also retains its original quality and detail.Finally, the user-friendly output interface allows for easy viewing, evaluation, and downloading of the colorized images. The system’s combination of advanced deep learning models, optimization techniques, and interactive features results in a powerful solution for high-quality grayscale image colorization across various applications, from historical restoration to digital content creation.

7.2 PERFORMANCE COMPARISON

Table 7.1. Performance Comparison of Algorithm

Feature	**GAN (e.g., Pix2Pix, CycleGAN)**	**CaffeModel (e.g., DeOldify CNN model)**
Algorithm Type	Generative Adversarial Network	CNN-based (trained in Caffe framework)
Architecture	Generator + Discriminator	Usually just a feed-forward CNN
Output Quality	More vibrant and realistic colorization	Often smoother and more stable but less vivid
Training Complexity	High (requires balancing G and D loss)	Moderate (single network)
Speed	Slower inference due to adversarial process	Faster, especially with pre-trained models
Generalization	Can produce diverse, imaginative outputs	Conservative, often limited to training data bias

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

The conclusion is an AI-driven grayscale image colorization system offers a comprehensive, efficient, and scalable solution for enhancing monochrome images with realistic and contextually accurate colors. By employing a multi-stage pipeline that integrates preprocessing, feature extraction, AI-based colorization, post-processing, and user interaction, the system ensures high-quality, visually appealing, and structurally accurate colorized images.The preprocessing module ensures that input grayscale images are prepared effectively, eliminating noise and standardizing the data for optimal performance. Feature extraction using CNNs and DCNNs enables the system to understand complex image structures, including textures, edges, and patterns, allowing for precise colorization. The core colorization process, powered by Generative Adversarial Networks (GANs), generates natural-looking colorizations through adversarial training between the generator and discriminator networks, ensuring high visual fidelity and coherence.Post-processing techniques such as histogram equalization and super-resolution further enhance the final output by improving vibrancy, contrast, and sharpness, ensuring that the colorized images maintain a high level of detail. The user-friendly interface facilitates easy evaluation, adjustment, and downloading of the results, making the system accessible for both professional and casual users.This AI-driven approach offers a powerful tool for a wide range of applications, from historical image restoration to medical imaging and digital content creation. The system's ability to handle large datasets efficiently, coupled with its ability to generate high-quality colorizations, makes it a versatile solution for industries requiring large-scale image processing. By overcoming the limitations of traditional and earlier machine learning-based colorization methods, this system provides a significant leap forward in grayscale image enhancement, paving the way for future advancements in AI-powered image processing technologies.

The process by down sampling during training and enhancing quality in post-processing. This approach allowed for practical model performance while maintaining strong visual results.

Another critical finding was the influence of dataset diversity on model success. Models trained on broader datasets performed better overall, though some rare or unusual colors posed difficulties. Future work could address this through data augmentation and specialized sub-models for niche datasets.

The results of this project have broad applications, from enhancing historical photos and films to aiding scientific visualization in fields like medical imaging and satellite analysis. Automated colorization not only saves time but also improves accessibility, helping modern audiences engage with black-and-white content.

8.2 FUTURE ENHANCEMENT

While the proposed AI-driven grayscale image colorization system already delivers high-quality results, several future enhancements can be implemented to further improve its accuracy, efficiency, and versatility. These improvements will expand the system’s capabilities and ensure its applicability across even broader domains. One key area for future enhancement is improving the model's generalization to handle a wider variety of image types, including those with complex and non-standard features. By incorporating transfer learning and expanding the training datasets to include more diverse image sources, the system can better adapt to different contexts, such as older, highly degraded images or those with unusual lighting conditions. Current processing times for colorization can be further reduced to enable real-time applications, such as in live video enhancement or interactive multimedia systems. Optimizing the underlying deep learning models and leveraging more efficient hardware, such as specialized AI processors (e.g., TPUs), can significantly improve processing speed without sacrificing quality, making it suitable for real-time content creation or restoration projects. Another potential enhancement is to incorporate context-aware colorization. By integrating more advanced AI models capable of understanding the semantic meaning behind an image (e.g., recognizing objects, scenes, or time periods), the system can produce more accurate color predictions that align better with historical accuracy or the specific context of the image. Offering users more control over the colorization process is another future enhancement. By allowing users to manually adjust color tones, brightness, or contrast during the colorization process, the system can cater to specific artistic or functional preferences, especially in fields like digital art, filmmaking, or product design. The system can be integrated with other advanced technologies, such as augmented reality (AR) and virtual reality (VR), to enable dynamic colorization in immersive environments. Additionally, incorporating cloud computing capabilities will allow for more scalable solutions, enabling the system to handle vast datasets and provide on-demand colorization services across different industries.

APPENDIX A

SOURCE CODE

```
import numpy as np
import cv2
import PySimpleGUI as sg
import os.path
version = '7 June 2020'
prototxt = r'model/colorization_deploy_v2.prototxt'
model = r'model/colorization_release_v2.caffemodel'
points = r'model/pts_in_hull.npy'
points = os.path.join(os.path.dirname(__file__), points)
prototxt = os.path.join(os.path.dirname(__file__), prototxt)
model = os.path.join(os.path.dirname(__file__), model)
if not os.path.isfile(model):
sg.popup_scrolled('Missing model file', 'You are missing the file
"colorization_release_v2.caffemodel"',
disk
pts = np.load(points)

# add the cluster centers as 1x1 convolutions to the model

class8 = net.getLayerId("class8_ab")
conv8 = net.getLayerId("conv8_313_rh")
pts = pts.transpose().reshape(2, 313, 1, 1)
net.getLayer(class8).blobs = [pts.astype("float32")]
net.getLayer(conv8).blobs = [np.full([1, 313], 2.606, dtype="float32")]
```

```
def colorize_image(image_filename=None, cv2_frame=None):
"""
Where all the magic happens.  Colorizes the image provided. Can colorize
either
a filename OR a cv2 frame (read from a web cam most likely)
:param image_filename: (str) full filename to colorize
:param cv2_frame: (cv2 frame)
:return: Tuple[cv2 frame, cv2 frame] both non-colorized and colorized
images in cv2 format as a tuple
"""
# load the input image from disk, scale the pixel intensities to the range [0,
1], and then convert the image from the BGR to Lab color space
image = cv2.imread(image_filename) if image_filename else cv2_frame
scaled = image.astype("float32") / 255.0
lab = cv2.cvtColor(scaled, cv2.COLOR_BGR2LAB)

# resize the Lab image to 224x224 (the dimensions the colorization network
accepts), split channels, extract the 'L' channel, and then perform mean
centering
resized = cv2.resize(lab, (224, 224))
L = cv2.split(resized)[0]
L -= 50

# pass the L channel through the network which will *predict* the 'a' and
'b' channel values
'print("[INFO] colorizing image...")'
net.setInput(cv2.dnn.blobFromImage(L))
ab = net.forward()[0, :, :, :].transpose((1, 2, 0))
```

# resize the predicted 'ab' volume to the same dimensions as our input image
ab = cv2.resize(ab, (image.shape[1], image.shape[0]))

# grab the 'L' channel from the *original* input image (not the resized one) and concatenate the original 'L' channel with the predicted 'ab' channels
L = cv2.split(lab)[0]
colorized = np.concatenate((L[:, :, np.newaxis], ab), axis=2)

# convert the output image from the Lab color space to RGB, then clip any values that fall outside the range [0, 1]
colorized = cv2.cvtColor(colorized, cv2.COLOR_LAB2BGR)
colorized = np.clip(colorized, 0, 1)

# the current colorized image is represented as a floating point data type in the range [0, 1] -- let's convert to an unsigned 8-bit integer representation in the range [0, 255]
colorized = (255 * colorized).astype("uint8")
return image, colorized

def convert_to_grayscale(frame):
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY) # Convert webcam frame to grayscale
gray_3_channels = np.zeros_like(frame) # Convert grayscale frame (single channel) to 3 channels
gray_3_channels[:, :, 0] = gray
gray_3_channels[:, :, 1] = gray
gray_3_channels[:, :, 2] = gray
return gray_3_channels

```
# --------------------------------- The GUI ---------------------------------

# First the window layout...2 columns

left_col = [[sg.Text('Folder'), sg.In(size=(25,1), enable_events=True
,key='-FOLDER-'), sg.FolderBrowse()],
[sg.Listbox(values=[], enable_events=True, size=(40,20),key='-FILE
LIST-')],
[sg.CBox('Convert to gray first',key='-MAKEGRAY-')],
[sg.Text('Version ' + version, font='Courier 8')]]

images_col = [[sg.Text('Input file:'), sg.In(enable_events=True, key='-IN
FILE-'), sg.FileBrowse()],
[sg.Button('Colorize Photo', key='-PHOTO-'), sg.Button('Start Webcam',
key='-WEBCAM-'), sg.Button('Save File', key='-SAVE-'),
sg.Button('Exit')],
[sg.Image(filename='', key='-IN-'), sg.Image(filename='', key='-OUT-')],]
# ----- Full layout -----
layout = [[sg.Column(left_col), sg.VSeperator(), sg.Column(images_col)]]

# ----- Make the window -----
window = sg.Window('Photo Colorizer', layout, grab_anywhere=True)

# ----- Run the Event Loop -----
prev_filename = colorized = cap = None
while True:
event, values = window.read()
if event in (None, 'Exit'):
```

```
break
if event == '-FOLDER-':         # Folder name was filled in, make a list of
files in the folder
folder = values['-FOLDER-']
img_types = (".png", ".jpg", "jpeg", ".tiff", ".bmp")
# get list of files in folder
try:
flist0 = os.listdir(folder)
except:
continue
fnames = [f for f in flist0 if os.path.isfile(
os.path.join(folder, f)) and f.lower().endswith(img_types)]
window['-FILE LIST-'].update(fnames)
elif event == '-FILE LIST-':    # A file was chosen from the listbox
try:
filename = os.path.join(values['-FOLDER-'], values['-FILE LIST-'][0])
image = cv2.imread(filename)
window['-IN-'].update(data=cv2.imencode('.png', image)[1].tobytes())
window['-OUT-'].update(data='')
window['-IN FILE-'].update('')

if values['-MAKEGRAY-']:
gray_3_channels = convert_to_grayscale(image)
window['-IN-'].update(data=cv2.imencode('.png',
gray_3_channels)[1].tobytes())
image, colorized = colorize_image(cv2_frame=gray_3_channels)
else:
image, colorized = colorize_image(filename)
```

```
window['-OUT-'].update(data=cv2.imencode('.png',
colorized)[1].tobytes())
except:
continue
elif event == '-PHOTO-':        # Colorize photo button clicked
try:
if values['-IN FILE-']:
filename = values['-IN FILE-']
elif values['-FILE LIST-']:
filename = os.path.join(values['-FOLDER-'], values['-FILE LIST-'][0])
else:
continue
if values['-MAKEGRAY-']:
gray_3_channels = convert_to_grayscale(cv2.imread(filename))
window['-IN-'].update(data=cv2.imencode('.png',
gray_3_channels)[1].tobytes())
image, colorized = colorize_image(cv2_frame=gray_3_channels)
else:
image, colorized = colorize_image(filename)
window['-IN-'].update(data=cv2.imencode('.png', image)[1].tobytes())
window['-OUT-'].update(data=cv2.imencode('.png',
colorized)[1].tobytes())
except:
continue
elif event == '-IN FILE-':      # A single filename was chosen
filename = values['-IN FILE-']
if filename != prev_filename:
prev_filename = filename
try:
```

```
image = cv2.imread(filename)
window['-IN-'].update(data=cv2.imencode('.png', image)[1].tobytes())
except:
continue
elif event == '-WEBCAM-':       # Webcam button clicked
sg.popup_quick_message('Starting up your Webcam... this takes a
moment....', auto_close_duration=1,  background_color='red',
text_color='white', font='Any 16')
window['-WEBCAM-'].update('Stop Webcam',
button_color=('white','red'))
cap = cv2.VideoCapture(0) if not cap else cap
while True:                # Loop that reads and shows webcam until stop button
ret, frame = cap.read()     # Read a webcam frame
gray_3_channels = convert_to_grayscale(frame)
image, colorized = colorize_image(cv2_frame=gray_3_channels)    #
Colorize the 3-channel grayscale frame
window['-IN-'].update(data=cv2.imencode('.png',
gray_3_channels)[1].tobytes())
window['-OUT-'].update(data=cv2.imencode('.png',
colorized)[1].tobytes())
event, values = window.read(timeout=0)  # Update the window outputs and
check for new events
if event in (None, '-WEBCAM-', 'Exit'): # Clicked the Stop Webcam button
or closed window entirely
window['-WEBCAM-'].update('Start Webcam',
button_color=sg.theme_button_color())
window['-IN-'].update('')
window['-OUT-'].update('')
break
```

```
elif event == '-SAVE-' and colorized is not None:   # Clicked the Save File button
filename = sg.popup_get_file('Save colorized image.\nColorized image be saved in format matching the extension you enter.', save_as=True)
try:
if filename:
cv2.imwrite(filename, colorized)
sg.popup_quick_message('Image save complete', background_color='red', text_color='white', font='Any 16')
except:
sg.popup_quick_message('ERROR - Image NOT saved!', background_color='red', text_color='white', font='Any 16')
# ----- Exit program -----
window.close()
```

APPENDIX B

SCREENSHOTS

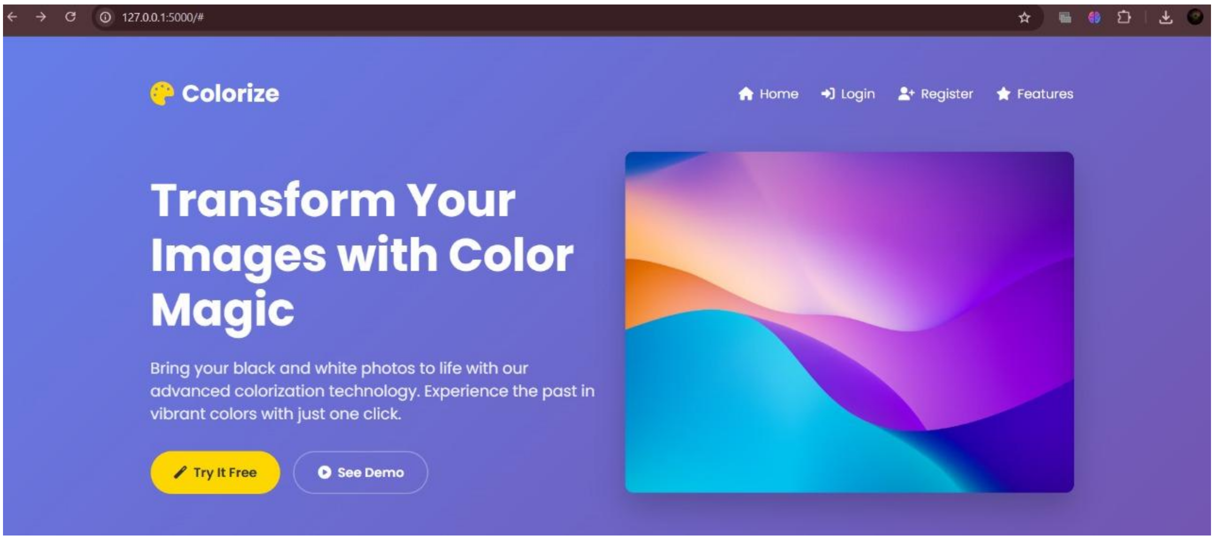

Fig B.1. Interface

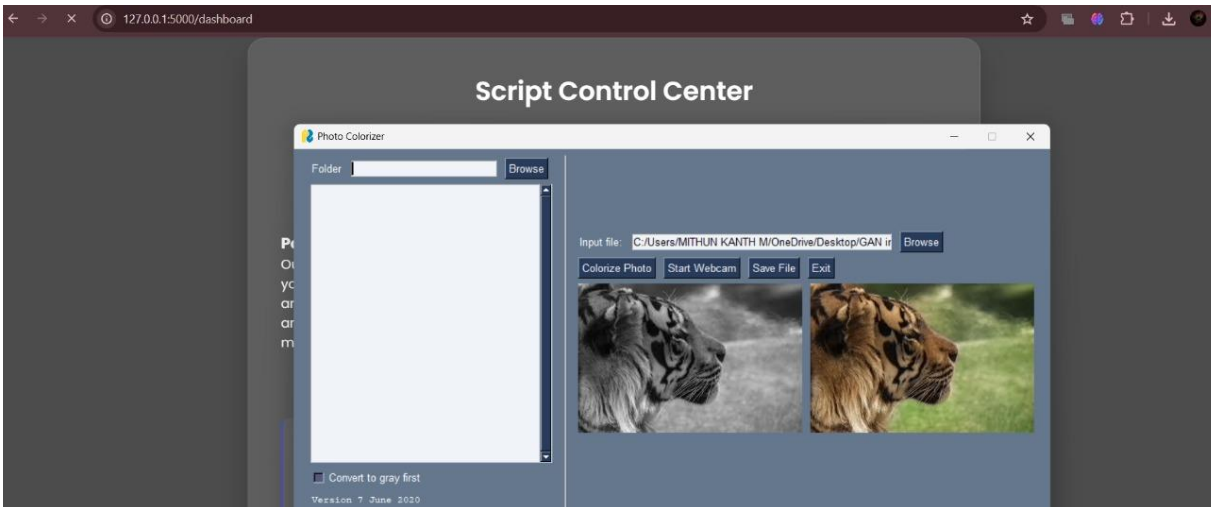

Fig B.2. Output

REFERENCES

1. Bogdan Kovalenko; Vladimir Lukin; Benoit Vozel,"MSE Prediction in BPG-Based Lossy Compression of Grayscale Images" IEEE 5th KhPI Week on Advanced Technology, 2024.
2. Yihang Wang; Minghang Xie; Xiaozhong Yang,"A novel method of grayscale image fusion based on discrete fractional wavelet transform combined with improved chaotic genetic algorithm" 5th International Conference on Computer Vision, Image and Deep Learning (CVIDL), 2024.
3. Vinish Kumar; Santosh Verma; Gaurav Raj,"Colorization of Grayscale Images Using Neural Network Without User Intervention" 3rd International Conference on Advancement in Electronics & Communication Engineering, 2023.
4. Arun Kumar; Anil Kumar; Amit Vishwakarma,"Multilevel Thresholding of Grayscale Complex Crop Images using Minimum Cross Entropy" 10th International Conference on Signal Processing and Integrated Networks, 2023.
5. Vladimira Ganchovska; Ivanka Krasteva,"Converting color to grayscale image using LabVIEW" International Conference Automatics and Informatics (ICAI), 2022.
6. Visaruth Punnium; Sitapa Rujikietgumjorn; Prapaporn Rattanatamrong,"Classifying Thai Occupation from Images using Deep Learning with Grayscale Feature Extractor" 19th International Joint Conference on Computer Science and Software Engineering, 2022.
7. Xinghua Cheng; Zhilin Li,"Using Boltzmann Entropy to Measure Scrambling Degree of Grayscale Images" IEEE 5th International Conference on Cryptography, Security and Privacy (CSP), 2021.

8. Ivana Žeger; Sonja Grgić."An Overview of Grayscale Image Colorization Methods" International Symposium ELMAR, 2020.
9. Wien Hong; Jeanne Chen; Pei-Shih Chang; Jie Wu; Tung-Shou Chen; Jason Lin,"A Color Image Authentication Scheme With Grayscale Invariance"IEEE Access, 2020.
10. Wenjie Liu; Lu Wang; Mengmeng Cui,"Quantum Image Segmentation Based on Grayscale Morphology" IEEE Transactions on Quantum Engineering ,2020.

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This is to certify that Prof./Dr./Mr./Ms. MUTHUKUMARAN of K RAMAKRISHNAN COLLEGE OF TECHNOLOGY has presented a paper titled ENHANCING GRAYSCALE IMAGES WITH AI-DRIVEN GENERATIVE MODELS in 2nd International Conference on Data Analytics and Intelligence Computing organized by the Department of Artificial Intelligence and Data Science, Velammal Institute of Technology, Chennai, TamilNadu, India on April 09, 2025.

COORDINATORS	HOD	VICE PRINCIPAL	PRINCIPAL
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