BASAVARAJESWARI GROUP OF INSTITUTIONS

BALLARI INSTITUTE OF TECHNOLOGY & MANAGEMENT

Autonomous Institute under VTU, Belagavi | Approved by AICTE, New Delhi Recognized by Govt. of Karnataka

NACC Accredited Institution*

(Recognized by Govt. of Karnataka, approved by AICTE, New Delhi & Affiliated to Visvesvaraya Technological University, Belagavi)

"JnanaGangotri" Campus, No.873/2, Ballari-Hospete Road, Allipur, Ballari-583 104 (Karnataka) (India)

Ph: 08392 – 237100 / 237190, Fax: 08392 – 237197

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

A Mini-Project Report On

"BLACK AND WHITE IMAGE COLOURIZATION"

Project Associates:

S Veerendra Swamy	**3BR22AI141**
Santhosh Patil	**3BR22AI145**
Satheesh N	**3BR22AI148**
Subhood M	**3BR22AI157**

Under the Guidance of

Ms. Shravani

Assistant Professor

Dept of AIML, BITM, Ballari

Visvesvaraya Technological University

Belagavi, Karnataka

2024-2025

BASAVARAJESWARI GROUP OF INSTITUTIONS

BALLARI INSTITUTE OF TECHNOLOGY & MANAGEMENT

NACC Accredited Institution*

(Recognized by Govt. of Karnataka, approved by AICTE, New Delhi & Affiliated to Visvesvaraya Technological University, Belagavi) "JnanaGangotri" Campus, No.873/2, Ballari-Hospete Road, Allipur, Ballari-583 104 (Karnataka) (India)

Ph:08392 – 237100 / 237190, Fax: 08392 – 237197

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

CERTIFICATE

This is to certify that the project work entitled "**Black and White Image Colourization**" is a bonafide work carried out by **S Veerendra Swamy 3BR22AI141, Santhosh Patil 3BR23AI145, Satheesh N 3BR22AI148, Subhood M 3BR22AI157** in partial fulfillment for the award of degree of **Bachelor Degree in AIML** in the **VISVESVARAYA TECHNOLOGICAL UNIVERSITY**, Belagavi during the academic year 2024-2025. It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The project has been approved as it satisfies the academic requirements in respect of mini project work prescribed for a Bachelor of Engineering Degree.

Signature of Project Guide	Signature of Coordinator	Signature of HOD
Ms. Shravani	**Mr. CTM Praveen Kumar**	**Dr. B. M. Vidyavathi**

TABLE OF CONTENTS

LIST OF FIGURES

ABSTRACT

This project presents an automated colorization system for black-and-white images using a deep learning approach. Leveraging a U-Net convolutional neural network, the model predicts color channels from grayscale inputs, delivering realistic and visually appealing results. By preserving the original image content and structure, the system provides a reliable solution for restoring and enhancing monochrome images, with potential applications in historical photo restoration, media production, and creative design.

ACKNOWLEDGEMENT

The successful completion of our mini-project, **“Black and White Image Colourization”**, would not have been possible without the support, guidance, and encouragement of several individuals. We express our heartfelt gratitude to everyone who contributed to the realization of this project.

We are deeply thankful to our guide, **Ms. Shravani**, for her invaluable support, guidance, and insightful suggestions throughout the project. We extend our sincere thanks to **Dr. B. M. Vidyavathi**, Head of the Department of AIML, for her encouragement and valuable input that greatly enhanced our work.

We also convey our gratitude to the **Principal**, **Management**, and the **non-teaching staff** for their continuous support and assistance during the project. Their cooperation and encouragement played a vital role in the successful completion of our mini-project.

CHAPTER 1

INTRODUCTION

Image colorization is a complex and challenging task that involves adding colour to grayscale images, often with limited or ambiguous information. Traditional colorization techniques were manual, relying on human intervention to select appropriate colours. Over time, automated methods have emerged, including rule-based approaches and, more recently, machine learning models that attempt to predict colours based on patterns in the data.

With the advent of deep learning, methods for image colorization have significantly evolved. Convolutional Neural Networks (CNNs) and more specialized architectures, such as U-Net and Generative Adversarial Networks (GANs), have shown promise in generating realistic colorizations for grayscale images. The U-Net model, initially designed for biomedical image segmentation, has been successfully adapted for other image-to-image tasks, including colorization (e.g., [Ronneberger et al., 2015]). U-Net's encoder-decoder structure with skip connections allows it to capture fine details necessary for high-quality colour restoration.

Previous work, such as Zhang et al. (2016), leveraged CNN-based approaches to predict the chrominance channels in the LAB colour space. GANs, as used in [Isola et al., 2017], have also shown the ability to produce convincing colorized outputs by learning to create realistic colour distributions. However, these models often require extensive training data and computational resources.

CHAPTER 2

Literature Survey

Iizuka et al. [1] In this paper he combined two networks, one to predict the global features of the input image and the other to specialize in local features of input images. The global features network is trained for image classification and directly concatenated to the local features network which are then trained for colorization of images using L2 Euclidean loss function.
Richard Zhang [2] In this paper he introduced an optimized solution by taking a huge data-set and single feed-forward pass in CNN. They used a custom multinomial cross entropy loss with class rebalancing and by using humans as subjects they were able to fool 32% of them by their results. They used prior color distribution obtained from the training set to predict a distribution for each output pixel.

Baldassarre et al. [3] In this paper he made a network model that combines a deep CNN architecture, that is trained from scratch, with a pre-trained model Inception-Resnetv2 for high level feature extraction. They train this network on a small subset of 60,000 images from ImageNet. This architecture is similar to that used by Iizuka et al. [1] and it also uses Euclidean (L2) loss function.

In [4] deep convolutional neural network architectures used are inherited from the VGG16 network. They implemented two models: one as a regression model and other as a classification model. They use the CIE LUV Colorspace for input and output. They posed it as a classification task that can produce colorized images which are much better than those generated by a regression-based model.

David Futschik[5] In this paper he made use of several variants of CNNs and compared their performance on the data, using two different NN architectures; one traditional, plain CNN, and other being inspired by residual CNNs, which had not been used for colorization previously. Despite the smaller fewer parameters, this model was able to generate results that surpass plain CNN in generalization to unseen/test data.

In [6], automatic image colorization with two different CNN models is proposed. They train a classification and regression model on CIFAR-10 dataset using Lab colorspace. They train the classification model from scratch and also by transfer learning from a pretrained VGG16 network. They also use the Annealed-mean technique with the model to map prediction distribution to single output prediction and show that it can produce vibrant and spatially.

Larsson et al. [7] In this paper They train their model on ImageNet dataset to predict per-pixel color histograms and made use of convolutional layers from VGG16 network layer to predict pixels' values, which are pre trained on the image classification task and fine-tuned for colorization.

Phillip Isola et al. [8] In this paper they defined a conditional GAN for image-to-image translational problem by putting a condition on the GAN to produce corresponding output data. This network learns a mapping between the input image and the output image and by using loss function during the training procedure of the mapping, great results were achieved. In this paper the generator model used “U-net" architecture and convolutional "PatchGAN" classifier for discriminator model.

CHAPTER 3

PROBLEM STATEMENT

To Automatic colorization of black-and-white images is a complex task due to the absence of color information. Manually adding colors is labor-intensive and subjective. Therefore, a model that can colorize grayscale images with minimal input provides an effective solution for large-scale applications in historical photo restoration, media, and personal photography enhancement.

CHAPTER 4

OBJECTIVES

- **Develop a Deep Learning-Based Image Colorization Mode**

  Design and implement a U-Net-based neural network to predict the color components (AB channels) of grayscale images in the LAB color space.

- **Utilize the CIFAR-10 Dataset for Model Training and Evaluation**

  Train the model on a well-known dataset of natural images (CIFAR-10) to learn effective colorization techniques for low-resolution (32x32 pixel) images.

- **Preprocess Images for Efficient Learning**

  Convert RGB images to LAB color space to separate luminance (L) from chrominance (AB), simplifying the color prediction task.

- **Quantitatively Evaluate Model Performance**

  Use the Structural Similarity Index (SSIM) to assess the perceptual and structural similarity between the colorized output and the original images.

- **Qualitatively Analyse Colorization Results**

  Visualize the colorized outputs and compare them against original color images to assess the model's ability to generate realistic and vibrant colors.

- **Provide a Generalizable Framework for Image Colorization**

  Test the model's ability to generalize by applying it to manually selected grayscale images outside the CIFAR-10 dataset. **Contribute to Research in Image-to-Image Translation**

CHAPTER 5

SCOPE OF THE PROJECT

The scope of this project is to develop an AI-based model that automates the colorization of black-and-white images, addressing the challenges of manual colorization, which is often labor-intensive, subjective, and time-consuming. The proposed system leverages advanced deep learning techniques, such as convolutional neural networks (CNNs), to generate realistic and vibrant colors with minimal manual input. This solution is designed for large-scale applications, including historical photo restoration for museums and archives, enhancement of media content like films and documentaries, and the transformation of personal black-and-white photographs into colorful, visually appealing images. By focusing on efficiency, scalability, and user-friendliness, the project aims to cater to professionals in media restoration, content creators, and individuals, contributing significantly to the fields of cultural preservation, media production, and personal photography.

CHAPTER 6

REQUIREMENTS

6.1 Functional Requirements

Image Input: The system allows to upload grayscale images in format (JPEG,PNG).

Colorization Process: The system must process the grayscale image using a deep learning model (e.g., CNN or GAN) to predict and apply appropriate colors.

Output Generation: Interacts seamlessly with other applications for task execution.

6.2 Non-Functional Requirements

Performance: Ensures minimal latency and high responsiveness in system operations.

Scalability: Supports increasing user demands without performance degradation.

Accuracy and Quality: The generated colorized images must be realistic and contextually accurate, preserving the details of the original grayscale input.

CHAPTER 7

DESIGN

7.1 Block Diagram

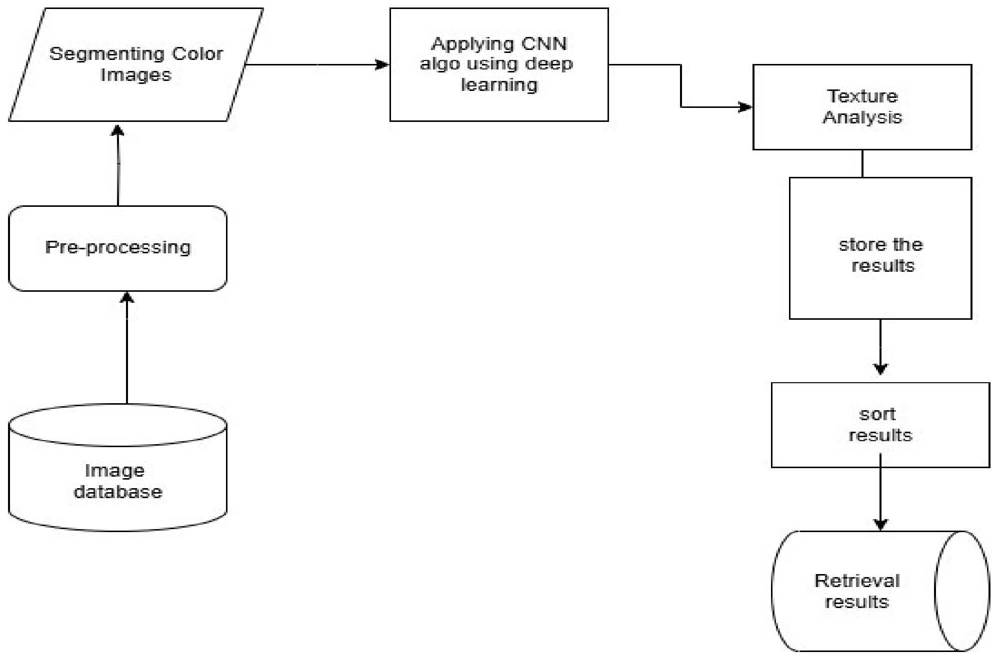

Fig: 7.1 Block Diagram

The block diagram represents the workflow of an image colorization system, starting with the **User Input**, where grayscale images are uploaded in standard formats like JPEG or PNG. The uploaded image goes through **Preprocessing**, where it is resized, normalized, and prepared for the deep learning model. The preprocessed image is then passed to the **Deep Learning Model** (e.g., CNN or GAN), which predicts and applies suitable colors based on its training. The output from the model is further refined in the **Post-Processing** stage to enhance colors and ensure a visually appealing result. Finally, the **Output Generation** stage provides the user with the colorized image, offering options to view, download, or save the processed image. This streamlined system ensures high-quality and realistic colorization of grayscale images.

7.2 Data Flow Diagram

Level 0 DFD

The **Level 0 DFD** provides a high-level overview of the system, showing its interactions with external entities without diving into internal processes.

Level 1 DFD

This level breaks the system into detailed processes and shows how data flows between components.

Processes and Data Flow:

1. Grayscale Image → Preprocessing → Preprocessed Image
2. Preprocessed Image → Feature Extraction → Feature Map.
3. Feature Map + Model Weights → Colorization Model → Initial Colorized Image.
4. Initial Colorized Image → Post-Processing → Final Colorized Image.
5. Final Colorized Image → User.

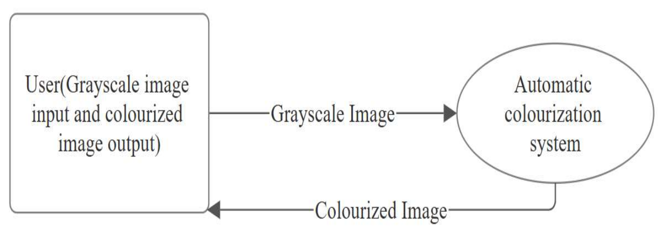

Fig: 7.2.1 Data Flow Diagram Level 0

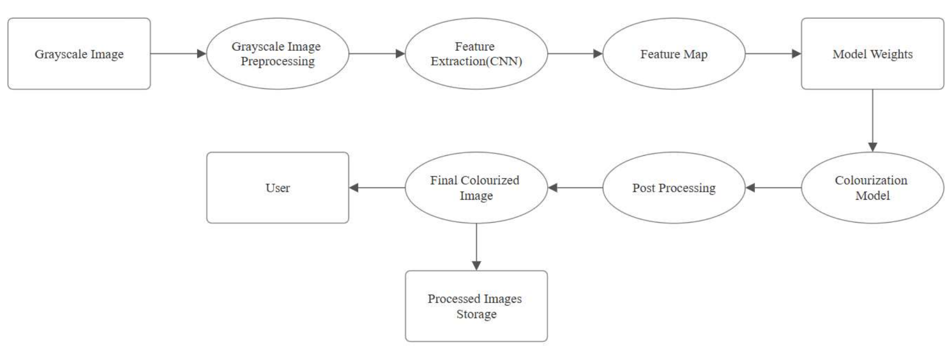

Fig 7.2.2 Data Flow Diagram Level 1

7.3 Use Case Diagram

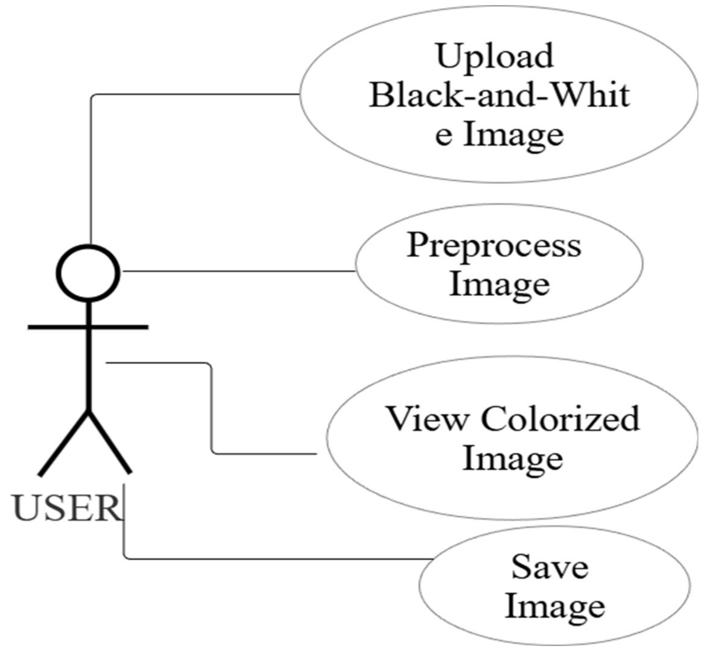

Fig: 7.3 Use case Diagram

The diagram illustrates a use case for an image colorization system from a user's perspective. The process begins with the **user uploading a black-and-white image**, which serves as the input for the colorization task. Once the image is uploaded, the system proceeds to the **preprocessing stage**, where the image is prepared for the colorization process. This step may involve resizing, normalization, or other transformations necessary to make the image compatible with the underlying model. After preprocessing, the system generates a colorized version of the image, and the user can proceed to **view the colorized image**. If satisfied with the result, the user has the option to **save the image** to their device for future use. This workflow provides an intuitive and user-friendly interface for automating the process of converting grayscale images into vibrant, colorized outputs.

7.4 Sequence Diagram

.

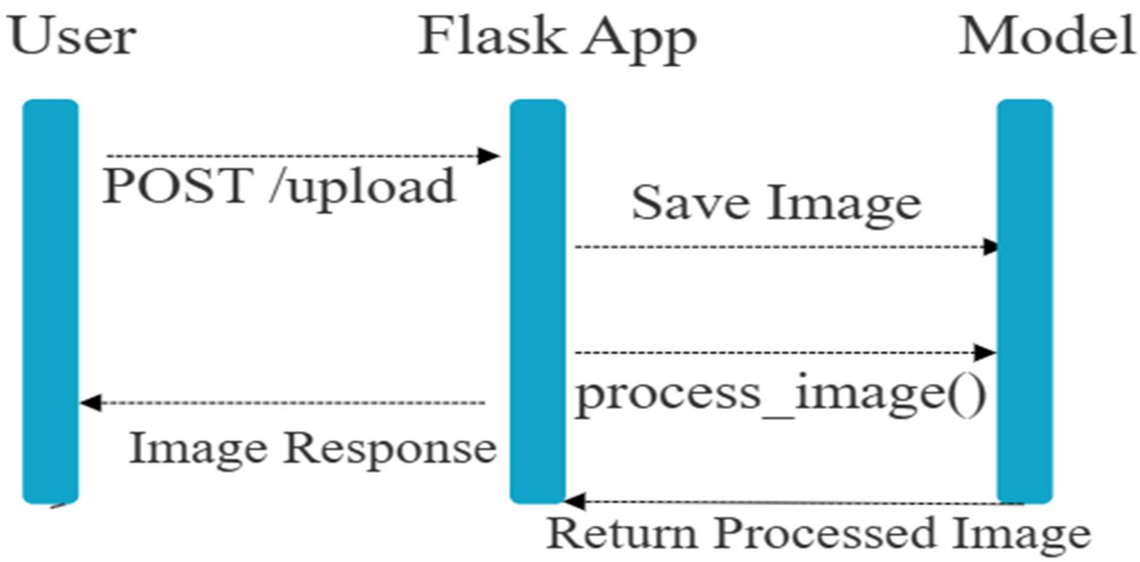

Fig: 7.4 Sequence Diagram

The diagram represents the workflow of an image colorization system implemented using a Flask application and a deep learning model. The process begins when the **user sends a POST request** to the /upload endpoint of the Flask app, attaching a grayscale image as input. Upon receiving the request, the Flask application **saves the uploaded image** to a designated location for further processing. Next, the Flask app calls the process_image() function, which interacts with the deep learning model to perform the colorization task. The model processes the grayscale image, generating a fully colorized version of the input. Once the colorization is complete, the Flask app **returns the processed image** to the user in response to their initial request. This interaction ensures a seamless flow, where users can easily upload grayscale images and receive high-quality, colorized outputs. The integration of Flask provides a simple yet efficient interface for deploying the model as a web service.

7.5 Activity Diagram

Wake Up: The assistant activates upon receiving a wake word or signal.

Wait for Query: The system listens for the user's input, which could be a command, question, or quit instruction.

Decision-Making:

If it's a command, the system executes the specified task.

If it's a question, the system processes and executes the query to provide an answer.

If the input is quit, the system responds with a goodbye message and ends the session.

Loop: The process restarts after executing a command or query, continuing to wait for new inputs.

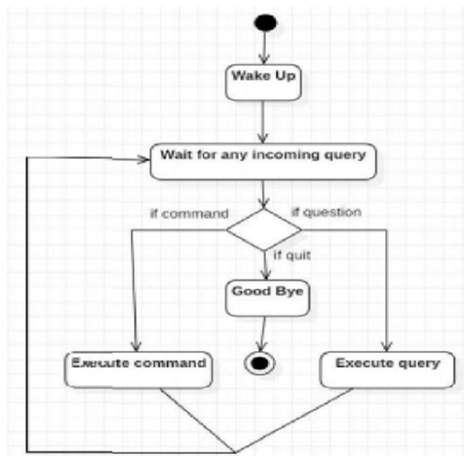

Fig: 7.5 Activity Diagram

CHAPTER 8

IMPLEMENTATION

8.1 Modules

- Input Handling Module
- Image Preprocessing Module
- Feature Extraction Module
- Colorization Model Module
- Post-Processing Module
- Model Weights and Configuration Module
- Error Handling Module
- Output Module

8.2 Describes Software Used

Machine Learning and Deep Learning Frameworks

TensorFlow: TensorFlow provides tools like Keras for easy model creation, while PyTorch offers flexibility in research and experimentation

Computer Vision Libraries

OpenCV: Used for image preprocessing tasks such as resizing, normalization, and format conversion

Data Manipulation and Analysis

Numpy: For handling numerical computations and working with arrays (image data).

Pandas: Used for organizing and analyzing tabular data, if any metadata is included (e.g., image filenames or annotations).

Visualization

Matplotlib: For visualizing model performance, intermediate outputs, and training metrics like loss curves.

CHAPTER 9

RESULTS AND DISCUSSION

The implementation of automatic colorization demonstrates promising outcomes in transforming grayscale images into visually appealing colored images. The model effectively captures basic color patterns and applies them to objects, landscapes, and human features with reasonable accuracy.

Frontend page:

Upload the image by drop or click to upload for black and white image click a image to colorize the given input

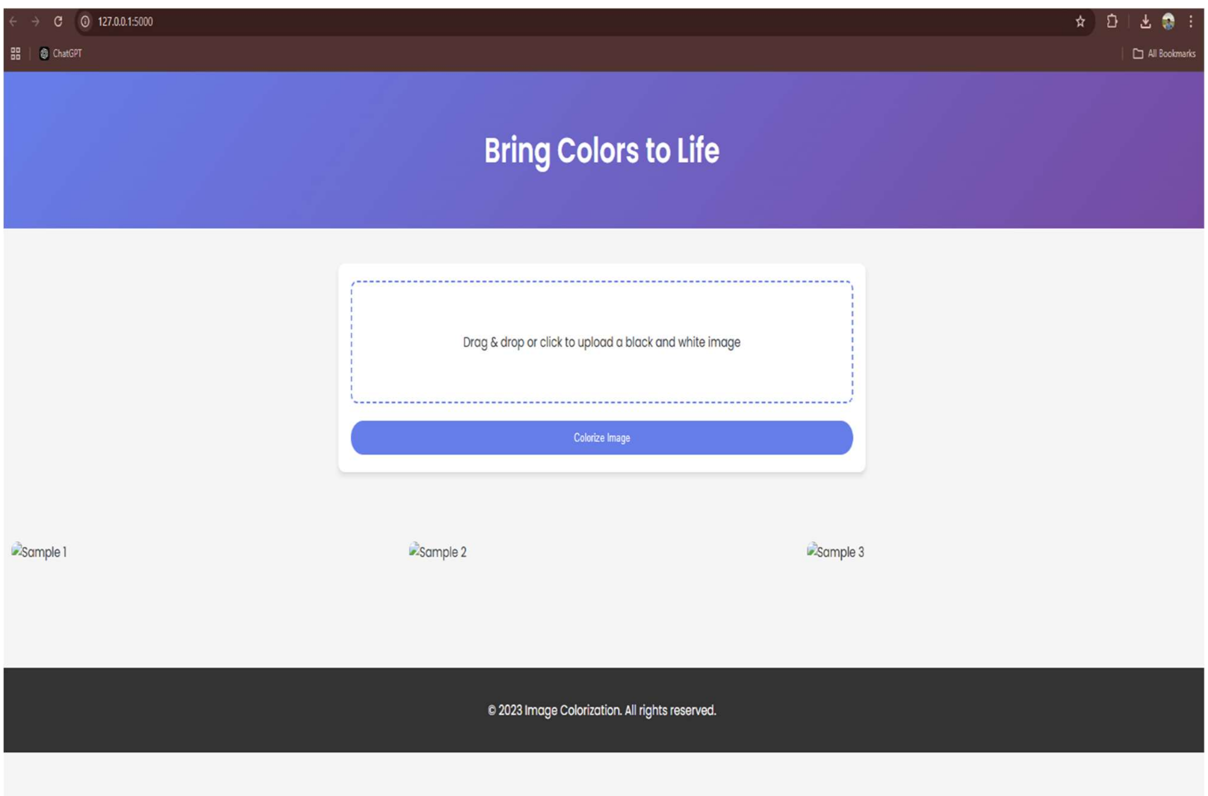

Fig 10.1

Input Image:

By giving the greyscale image as a input click a button to colourize the picture.

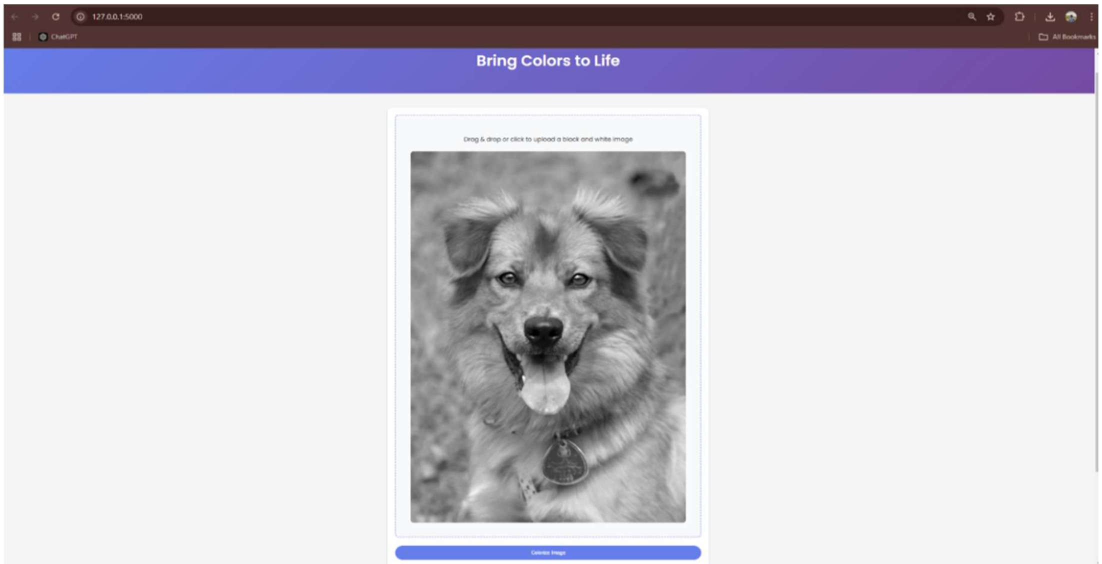

Fig 10.2

Output Image:

The colourized image is displayed if we want to save the image then click on butoon save option.

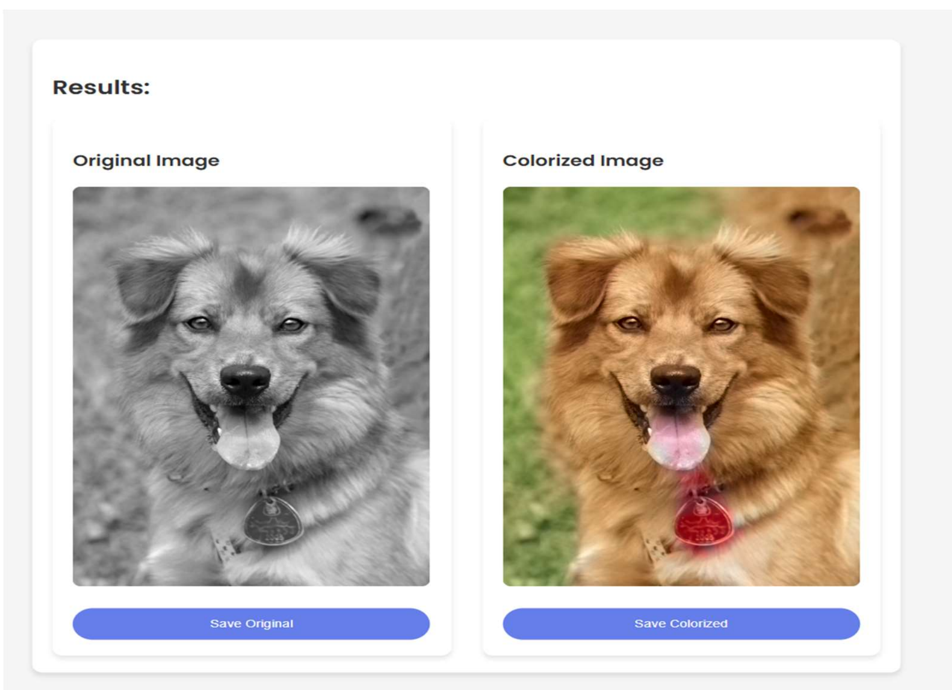

Fig 10.3

CHAPTER 10

ADVANTAGES AND DISADVANTAGES

12.1 ADVANTAGES

- **Time Efficiency**
- **Scalability**
- **Cost-Effective**
- **Enhanced Accessibility**
- **Realism and Engagement**

12.2 DISADVANTAGES

- **Lack of Accuracy**
- **Subjectivity**
- **Limited Context Understanding**

CHAPTER 11

APPLICATIONS

- **Historical Photo Restoration**
- **Media and Entertainment**
- **Personal Photography**
- **Educational Content**
- **Art and Creative Projects**

CHAPTER 12

CONCLUSION

By utilizing a U-Net convolutional neural network, the system effectively predicts the color channels from grayscale inputs, ensuring that the colorized outputs are both realistic and visually appealing. The model's ability to preserve the original content and structure of the images enhances its reliability and makes it a valuable tool for various applications. Automatic colorization of black-and-white images bridges the gap between historical grayscale photos and vibrant modern visuals. By leveraging advanced machine learning models, this process transforms the labor-intensive and subjective task of manual coloring into an efficient and scalable solution. This innovation holds significant potential for applications in historical restoration, media production, and personal photography enhancement, enabling the preservation and enrichment of visual memories with minimal effort.

CHAPTER 13

Future Scope

The future of automatic colorization of black-and-white images holds immense potential across various domains. Advancements in AI and deep learning are expected to enhance the realism and precision of colorized outputs, making them indistinguishable from true-colored images. User-controlled customization features can provide greater flexibility, allowing individuals to fine-tune colors and styles according to their preferences. Real-time colorization of videos and live streams is also a promising avenue, facilitated by faster computing and cloud-based technologies. Integration with augmented reality (AR) and virtual reality (VR) can create immersive experiences, especially in education, tourism, and entertainment. Beyond photographs, this technology could be applied to domains like medical imaging, satellite imagery, and scientific visualization, where adding color can provide valuable insights. For historical research and cultural preservation, automatic colorization can assist in restoring large volumes of archival images while respecting cultural and regional nuances. Furthermore, the development of self-learning models can reduce the dependency on labeled datasets, enabling more adaptive and efficient learning. These advancements position automatic colorization as a transformative tool with wide-ranging applications in the future.

REFERENCES

[1] Satoshi Iizuka, Edgar Simo-Serra, and Hiroshi Ishikawa. "Let there be Colour!: Joint End-to-end Learning of Global and Local Image Priors for Automatic Image Colorization with Simultaneous Classification". ACM Transaction on Graphics (Proc. of SIGGRAPH), 35(4):110, 2016.

[2] R. Zhang, P. Isola, and A. A. Efros, "Colorful image colorization," in ECCV, 2016.

[3] Nazeri, E. Ng, and M. Ebrahimi, "Image colorization using generative adversarial networks," in International Conference on Articulated Motion and Deformable.

[4] Alex Avery and Dhruv Amin, "Image Colorization".CS230 – Winter 2018.

[5] David Futschik, "Colorization of black-and-white images using deep neural networks", January 2018.

[6] Jeff Hwang and You Zhou, "Image Colorization with Deep Convolutional Neural Networks", Stanford University.