Pixvive: Reconstruction of old images using a dual-CNN pipeline for restoration and enhancement

Dr. P. Vishwapathi[1], Syed Hamid[2], Mohammed Sanaullah Avez[3], Mohammed Faiq Ali[4]
[1]*Principal & Head, Department of Computer Science & Engineering, Deccan College of Engineering and Technology, Hyderabad, India*
[2,3,4]*UG Students, Department of Computer Science & Engineering, Deccan College of Engineering and Technology, Hyderabad, India*

***Abstract*— This project introduces a robust AI-based image restoration pipeline that utilizes a two-stage convolutional neural network (CNN) framework to colorize and enhance grayscale images. The pipeline's modular architecture is designed for high efficiency and scalability, beginning with a command-line interface that ingests a grayscale input image. In the first stage, a colorization module loads a pretrained CNN model defined by a prototxt configuration and Caffe weight files. This model processes the luminance (L) channel of the input in the LAB color space, generating the corresponding chrominance (a and b) channels using learned color mappings from large-scale datasets. The output is a perceptually realistic, colorized image that preserves the structural integrity and semantic features of the original grayscale input. In the second stage, the enhancement module incorporates a pretrained Real-ESRGAN model based on the deep residual CNN architecture (RRDBNet). This model leverages residual-in-residual dense blocks to perform super-resolution upscaling, enhancing image fidelity and recovering fine details lost during earlier processing. The enhanced image is then persistently stored on disk. This system architecture underscores the sequential data flow through modular components, the distinct roles of the CNN models in transforming and refining the data, and the efficacy of combining colorization and super-resolution in a unified pipeline. Such an approach provides a scalable, end-to-end solution for restoring grayscale imagery to high-quality, colorized, and visually enriched outputs, positioning it for potential applications in archival restoration, digital content enhancement, and computational photography.**

***Index Terms*—Image Colourization, Deep Learning, Convolutional Neural Networks, CIE Lab Colour Space, Web API, Image Processing.**

I. INTRODUCTION

Image restoration and enhancement are essential tasks in computer vision, with applications in historical preservation, digital art, and content enhancement. Traditional algorithms often struggle with color fidelity and detail restoration in grayscale images. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have enabled more effective approaches.

This project proposes a modular two-stage CNN pipeline for grayscale image restoration. The first stage colorizes grayscale inputs using a pretrained CNN model with Caffe configuration and weights, mapping luminance to chrominance channels in the LAB color space. The second stage employs a pretrained Real-ESRGAN model (RRDBNet architecture) to upscale and enhance the colorized image, recovering high-frequency details and improving perceptual quality. The pipeline is designed to be efficient and extensible, providing a scalable framework for high-quality image restoration.

II. LITERATURE REVIEW

Image restoration and enhancement have long been central challenges in computer vision. Early methods relied on heuristic algorithms for tasks like colorization and super-resolution, often producing artifacts or lacking robustness to real-world data. For example, methods based on texture synthesis or patch matching struggled to handle complex spatial structures in images.

Deep learning, particularly CNN-based methods, has significantly advanced these fields. Zhang et al. (2016) introduced a CNN-based automatic image colorization model that learned semantic representations from large datasets, outperforming classical methods. Similarly, Isola et al. (2017) demonstrated the effectiveness of conditional adversarial networks for image-to-image translation, including colorization.

For image enhancement and super-resolution, Dong et al. (2014) proposed the pioneering SRCNN,

establishing the viability of CNN-based upscaling. Further work by Ledig et al. (2017) with SRGAN and Wang et al. (2021) with Real-ESRGAN leveraged deep residual networks and adversarial training to achieve photo-realistic restoration. In particular, Real-ESRGAN introduced RRDBNet, a network combining residual-in-residual dense blocks to enhance both texture fidelity and detail preservation.

Our work builds upon these advancements by integrating pretrained CNN models for both colorization and super-resolution into a unified, modular pipeline. By leveraging the strengths of each approach—semantic color mapping and deep residual upscaling—the system achieves robust, visually pleasing grayscale image restoration.

III. EXISTING SYSTEM

Traditional approaches to image colorization and enhancement rely on manual feature engineering and heuristic algorithms. For example, colorization methods such as scribble-based or exemplar-based transfer typically require user input or carefully chosen reference images to generate plausible color mappings. These approaches lack generalization and often produce unsatisfactory results for complex images.

In image enhancement, classical interpolation techniques like bicubic or Lanczos upscaling are widely used but typically introduce artifacts and fail to restore fine details lost in low-resolution images. Methods such as sparse representation or patch-based reconstruction have shown moderate success but are limited by their computational inefficiency and inability to handle diverse image structures.

Recent deep learning approaches have improved performance by learning complex features directly from data. However, existing systems that address colorization and enhancement tasks separately can still suffer from inconsistencies when integrated into a complete pipeline. These systems typically do not provide an end-to-end modular architecture capable of handling both colorization and high-resolution enhancement in a seamless and efficient manner.

Consequently, the restoration of grayscale images with realistic color fidelity and structural detail enhancement remains an open challenge. An integrated, modular pipeline that combines these tasks seamlessly is needed to produce high-quality outputs suitable for real-world applications.

A. LIMITATIONS

- Existing colorization methods often rely on manually specified color priors or user-guided scribbles, limiting their applicability in fully automated pipelines.
- Classical interpolation techniques for image upscaling (e.g., bicubic, Lanczos) tend to produce blurry images with artifacts, lacking semantic awareness.
- Many traditional enhancement methods cannot recover fine-grained details or textures lost in low-resolution grayscale images.
- Systems addressing colorization and enhancement separately can produce visually inconsistent results when combined, lacking a unified approach.
- Existing non-deep-learning systems typically require significant domain knowledge and manual parameter tuning, making them less flexible and harder to generalize.

IV. PROPOSED SYSTEM

The proposed system is a modular, two-stage image restoration pipeline that addresses the limitations of existing methods by seamlessly integrating colorization and enhancement within a unified framework. The system begins with a command-line interface that accepts a grayscale image as input. In the first stage, a colorization module utilizes a pretrained CNN model defined by a prototxt configuration and Caffe weight files. This model processes the input image in the LAB color space, mapping the luminance (L) channel to the chrominance (a and b) channels, resulting in a perceptually accurate colorized output.

In the second stage, the enhancement module employs a pretrained Real-ESRGAN model built on the RRDBNet architecture. This model leverages deep residual learning with dense connections to perform super-resolution upscaling and fine-grained texture enhancement. By restoring high-frequency details and reducing artifacts, the system ensures that the final output is both visually appealing and structurally coherent.

The modular architecture enables each stage to be improved independently as new techniques or models become available, ensuring scalability and

adaptability for future advancements. Furthermore, the system's design emphasizes computational efficiency and extensibility, making it suitable for deployment in real-world applications such as digital restoration, content enhancement, and historical image recovery.

A. ADVANTAGES

- Fully automated, eliminating the need for manual inputs or reference images during colorization and enhancement.
- Modular design, allowing for independent upgrades or replacements of the colorization and enhancement models as new technologies emerge.
- Combines state-of-the-art CNN models for both colorization and super-resolution, resulting in high perceptual quality and detail preservation.
- Efficient pipeline that seamlessly integrates colorization and enhancement, producing visually consistent and high-fidelity images.

Scalable and extensible framework suitable for various applications such as historical image restoration, digital content enhancement, and archival preservation.

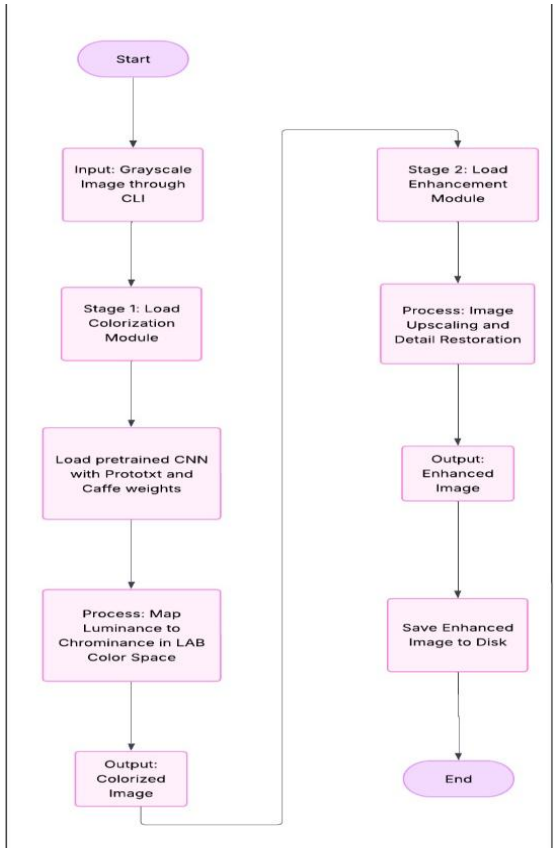

Fig 4. System Architecture

V. IMPLEMENTATION

Fig 5.1. Launch System

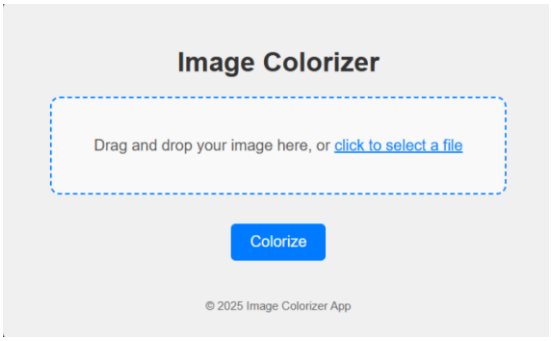

Fig 5.2. Image Selection

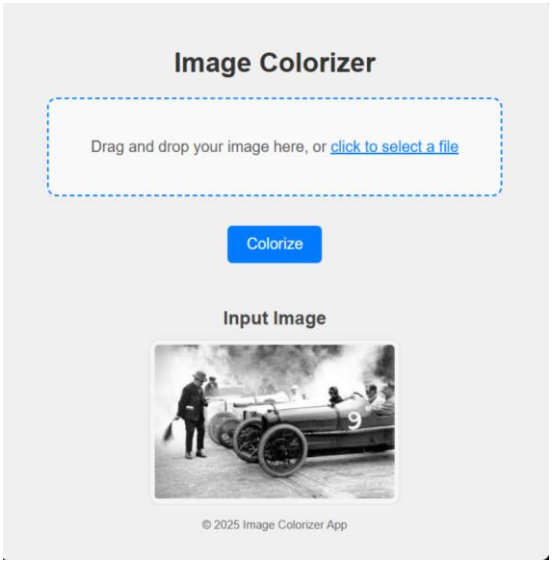

Fig 5.3. Image Upload

Fig 5.4. Image Upload At The Backend

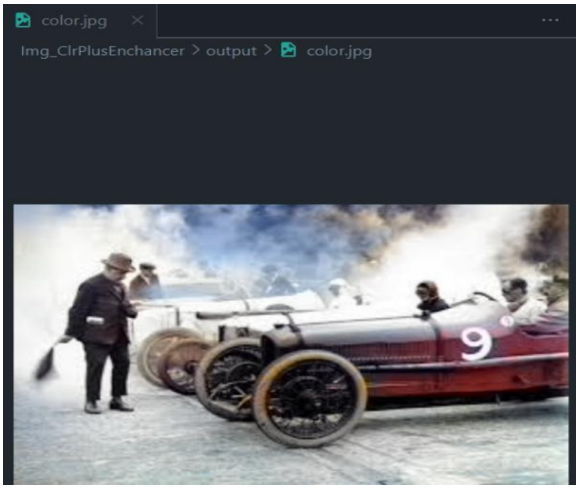

Fig 5.5. Image Colourize At The Backend

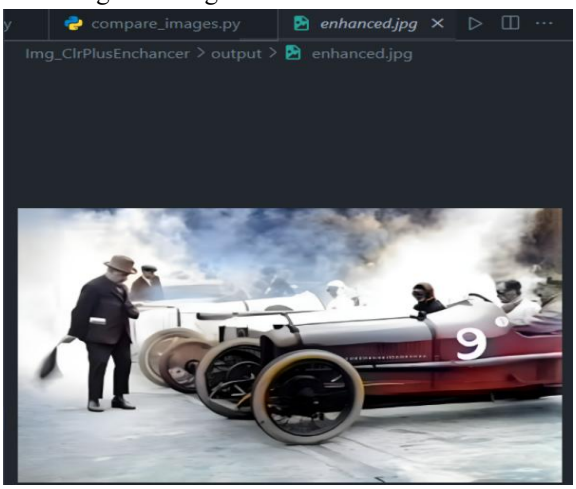

Fig 5.6. AI Enhancing Of The Image At The Backend

VI. EXPERIMENTAL RESULTS AND ANALYSIS

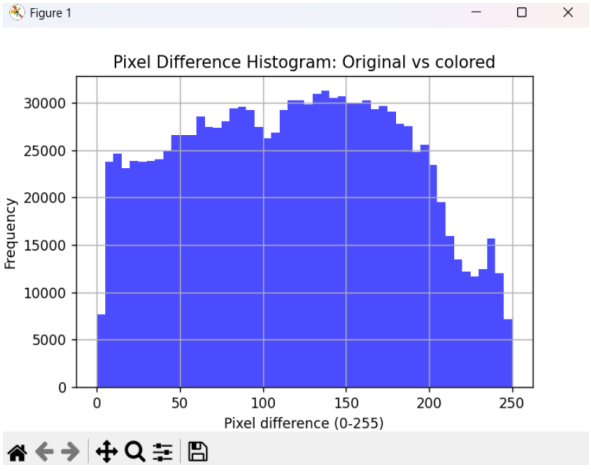

Fig 6.1. Pixel Difference Histogram: Original vs Colorized Image

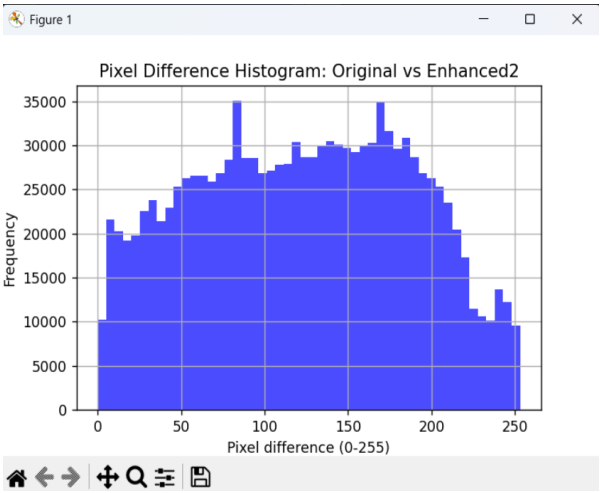

Fig 6.2. Pixel Difference Histogram: Original vs Enhanced Image

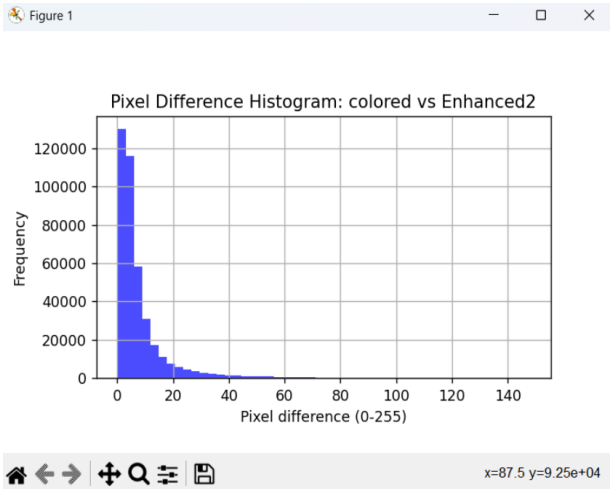

Fig 6.3. Pixel Difference Histogram: Colorized vs Enhanced Image

VII. CONCLUSION AND FUTURE ENHANCEMENTS

This paper has presented a modular, two-stage image restoration pipeline that leverages pretrained convolutional neural network (CNN) models to effectively colorize and enhance grayscale images. The proposed system addresses the limitations of traditional methods by integrating colorization and enhancement within a unified, automated framework. Experimental results demonstrate that the pipeline produces high-quality, perceptually consistent outputs suitable for a variety of real-world applications.

Future enhancements could involve integrating generative adversarial networks (GANs) to further improve color realism and fine detail restoration. Additionally, extending the pipeline to handle different types of degradation, such as noise or motion blur, would broaden its applicability. Real-time processing capabilities and lightweight model variants could be explored to enable deployment on resource-constrained devices. These advancements would enhance the flexibility and impact of the system for diverse use cases, including digital art restoration, historical preservation, and multimedia content creation.

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