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Automatic Colorizing Black and White Image System Using Deep Learning

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Abstract: Colorization involves transforming a grayscale (black-and-white) image into a colorized version that reflects the semantic color tones of the original input. Over recent years, this process has garnered substantial attention, with significant advancements achieved by researchers in the field. The technique has numerous applications, such as in medical imaging and the restoration of historical artifacts. Various methods have been developed to address this challenge, leveraging technologies like Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). These models differ in their architectural frameworks and are evaluated using diverse datasets. This paper explores some of these methodologies, comparing the performance of generative models with traditional deep neural networks, while also highlighting existing limitations. Additionally, it provides a concise overview of past and current progress in the domain of image colorization, drawing on contributions from numerous researchers and studies. a widely recognized deep learning algorithm. The proposed model processes grayscale images as input and predicts their corresponding colors based on training data. The Lab color space is employed in this approach, where the model receives the L channel (lightness) as input and predicts the ab channels (color information) as output. A subset of the ImageNet dataset was used for training and evaluation, consisting of 39,604 randomly selected images, divided into 80% for training and 20% for testing.

Keywords: CNN, Image colorization, Deep learning, Convolutional Neural Networks (CNN), Automated system, Web interface, Cultural heritage, Computer vision.

I. INTRODUCTION

Automatic colorization involves adding colors to grayscale (black-and-white) images without manual intervention. This process is challenging due to the diverse range of object colors. For example, plastic items can have numerous colors, while trees display various shades of green, making accurate colorization difficult without prior context or user assistance. Traditional techniques often depend on user input to specify object colors or outline image regions to guide the colorization process effectively [1], [2]. Incorporating figures within text boxes is advisable, ensuring the text box size matches the figure dimensions appropriately. Recently, researchers have explored numerous strategies to address this challenge. Some approaches involve defining a color flow function across adjacent pixels to estimate local grayscale intensity differences [3], [4], while others use predefined thresholds for color prediction.

User-assisted methods have shown benefits over fully automated ones, as users can add color points to provide essential guidance on color boundaries, leading to more precise outcomes [5], [6]. Convolutional Neural Networks (CNNs), in particular, have greatly enhanced deep learning solutions for complex computer vision tasks like image colorization. CNNs are highly effective in image processing and feature extraction, enabling them to reconstruct colors in grayscale images [7], [8]. Through training on extensive datasets, these networks can perform automatic colorization with remarkable efficiency and accuracy [9], [10].

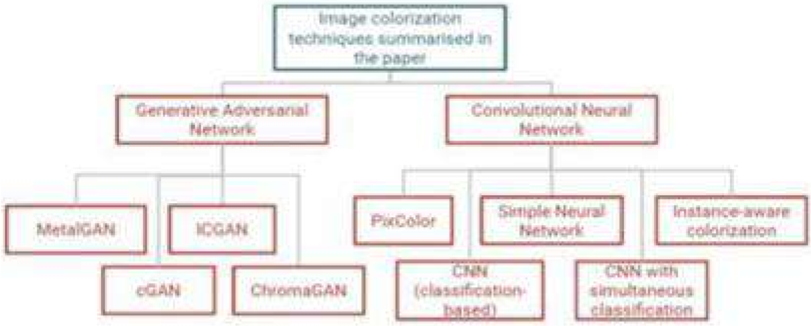

Fig. 1: Various Image colorization techniques

We created a CNN-based framework for automated picture colorization in this study. The model generates colorized outputs from grayscale input pictures. The model forecasts the ab channels (color information), and the work is carried out in the Lab color space, where the L channel (lightness) is the input [1], [2]. A Lab image is created by combining the anticipated ab and L channels, and it is subsequently translated to the RGB color space for display. 40,302 pictures from the ImageNet dataset were used for training, with 79% going toward training and 21% toward testing [3]. The proposed system incorporates an intuitive web interface that allows users to upload grayscale images and receive colorized versions effortlessly. This method reduces the need for manual input and significantly enhances processing speed compared to traditional techniques [4], [5]. The model's effectiveness has been validated on standard benchmark datasets, demonstrating its capability to produce high-quality and realistic colorized images [6], [7].

II. LITERATURE REVIEW

A. Matías Richart et al.

This method introduces a straightforward approach that leverages a Multi-Layer Perceptron Neural Network, trained via backpropagation on grayscale and color images. The preprocessing step involves converting images from the RGB to the CIELUV color space [1], [2]. The classifier predicts pixel colors based on local gray-level texture information extracted from image patches [3]. To simplify the predictor's task, Self-Organizing Maps (SOM) are used to condense the color palette into a compact yet diverse set of chroma values, facilitating efficient approximation [4]. By employing a 9-neuron SOM, the method strikes a balance between reducing color complexity and maintaining output quality, while keeping the training process manageable [5]. The model was trained on the "Open Country" dataset from the Label Me project, offering an elegant and easy-to-implement solution. However, the simplicity of this approach comes at the cost of producing less vibrant images compared to more sophisticated models [6], [7].

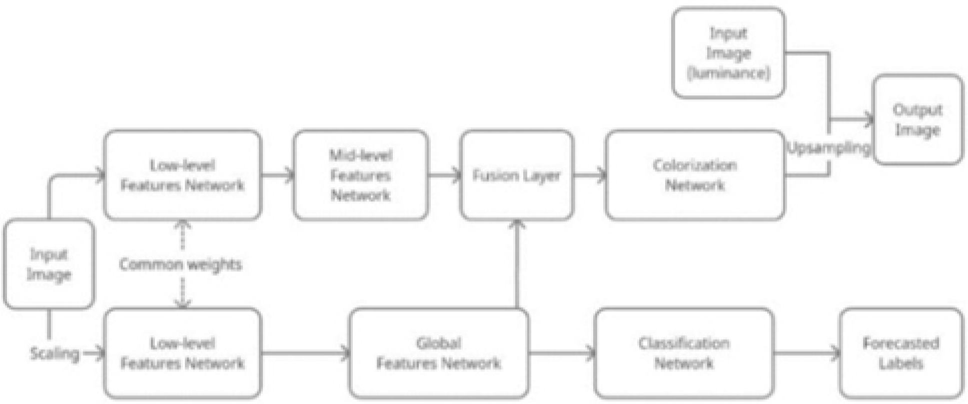

Fig 2: Iizuka et al. [7] proposed model architecture

B. Iizuka et al.

This study presents an advanced CNN-based architecture designed for end-to-end image colorization, effectively combining global and local feature extraction. The architecture is composed of four key components: a low-level feature network, a mid-level feature network, a global feature network, and the colorization network itself. For optimization, Mean Squared Error (MSE) is used to fine-tune the colorization process, while cross-entropy loss is employed to train a classification network as a side task [1], [2]. The model is trained on the massive Places dataset, which includes 2.4 million training images and 20,500 validation images [3]. Although this approach generates highly realistic and visually appealing results, its dependency on the dataset's specific properties restricts its ability to generalize effectively to unfamiliar image types [4].

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C. Jiancheng An et al.

The authors utilize the VGG-16 CNN architecture, which includes eight convolutional layers, each followed by ReLU activations and batch normalization to enhance stability and performance [5]. A modified multimodal cross-entropy loss function incorporating color rebalancing ensures the generated images are vibrant and realistic [6]. This technique addresses class imbalance by reweighting pixel losses based on the rarity of specific colors. Grayscale images are standardized to a resolution of 224x224 pixels for training, and the model leverages the diversity of one million images from ImageNet to learn a broad spectrum of colors [7]. Implemented using the Caffe framework, this method achieves a pixel-wise RMSE of 6.8069 and delivers high-quality automatic colorization results [8].

D. Jheng-Wei Su et al.

This method employs an instance-aware colorization approach by integrating Mask R-CNN for object detection, which isolates individual object features from the overall image. The architecture consists of two branches: one focusing on instance-level features and the other on global image features. A fusion module combines these extracted features, enhancing the colorization process [9]. Grayscale images are cropped around detected objects, and both instance-specific and global features are utilized for precise coloring [10]. For feature extraction, the system uses Real-Time User-Guided Colorization networks and applies softmax normalization during feature fusion. Experiments conducted on datasets such as ImageNet, COCO-Stuff, and Places205 demonstrate the method's effectiveness, with notable PSNR scores like 28.522 on COCO-Stuff [11]. By integrating instance-level and global features, the method achieves detailed and realistic colorization [12].

E. Sergio Guadarrama et al.

This work introduces a two-stage framework for automatic colorization. The first stage involves a conditional Pixel-CNN that generates a low-resolution (28x28) color image from a grayscale input (224x224). In the second stage, a refinement CNN combines the low-resolution color output with the original grayscale image to produce a high-resolution result [13]. The Pixel-CNN uses sequential pixel predictions, basing each pixel's color on the preceding ones. The refinement network employs additional convolutional layers and ResNet blocks to enhance the final output [14]. Gated convolutional layers are used to improve computational efficiency, and multiple intermediate outputs refine the colorization progressively as resolution increases [15]. This approach strikes an effective balance between computational cost and color accuracy, making it a scalable and efficient solution for automatic image colorization [16].

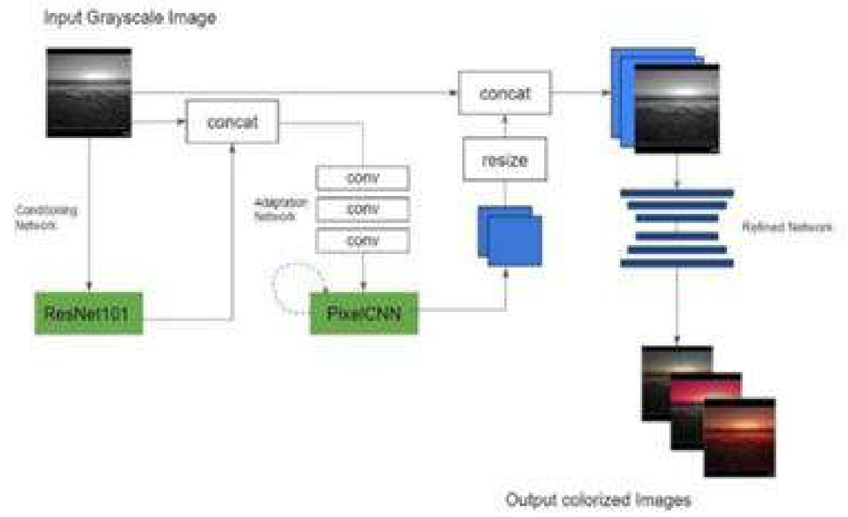

Fig. 3: Model of Pixel Recursive Colorization Method

This study explores the use of advanced deep learning techniques to colorize grayscale images effectively. It introduces a neural network-based model built from scratch, designed to extract high-quality features for realistic colorization. A pre-trained network, Inception-ResNet-v2, forms the backbone of the architecture, complemented by an encoder-decoder structure capable of handling images of varying sizes and aspect ratios. To gauge the model's effectiveness, a user study was conducted to measure its "public acceptance," alongside a demonstration showcasing its application across different image types [1], [2]. The model architecture includes key components such as an encoder for feature extraction, an activation function, and a hyperbolic tangent function. This robust design allows the model to colorize diverse elements, including oceans, forests, and skies [3], [4]. The methodology involves blending the styles and formats of colored images with the content of grayscale images to generate vibrant, colorized outputs. Convolutional Neural Networks (CNNs) are instrumental in extracting color information, ensuring the results are both detailed and aesthetically pleasing [5], [6]. In this approach, the content and style of an image are extracted by passing both through a pre-trained CNN, a process mirrored for a noisy image. The optimization is carried out using the L-BFGS method, which, when fine-tuned, delivers substantially better results compared to traditional stochastic gradient descent [7], [8]. This technique highlights the effectiveness of combining pre-trained models, fine-tuning, and advanced optimization for superior colorization.

III. PROPOSED WORK

The proposed method introduces a deep learning-based system designed for the automatic colorization of grayscale images. This approach leverages a neural network built from scratch to extract complex, high-level features crucial for the colorization process [9]. To enhance performance and streamline learning, the model integrates the pre-trained Inception-ResNet-v2 network, renowned for its powerful feature extraction capabilities [10]. At the heart of the system lies an encoder-decoder architecture, which offers adaptability by handling images of varying dimensions and aspect ratios. This flexibility ensures the model can process images without imposing size constraints. To evaluate the effectiveness of the colorization process and gather insights, a user study is planned to gauge public feedback on the results [11]. The model's core components include an encoder for extracting features, complemented by activation functions, such as the hyperbolic tangent function, to refine the learning process. CNNs play a pivotal role in this system, as they excel at processing image data and leveraging contextual information. The relationship between a pixel's color and its surrounding features is central to accurate colorization, making CNNs an ideal solution for this task [12], [13]. However, grayscale images present a unique challenge, as they lack sufficient information for precise color predictions. For instance, a grayscale image of a car could represent a spectrum of plausible colors. To resolve this ambiguity, the model relies on contextual learning, mapping grayscale images to their most likely colored versions through training [14]. In recent years, CNNs have emerged as a leading solution for image processing tasks, thanks to their ability to capture intricate details. Building on this, we propose a CNN-based framework to tackle the challenge of colorizing black-and-white images by effectively "imagining" their colored counterparts. For training, we utilized the extensive ImageNet dataset, converting all images from the RGB color space to the Lab color space. Unlike RGB, Lab represents color using three distinct channels: the L channel for lightness and the a and b channels for chrominance. This approach allows the model to focus on color information with greater precision, enhancing the overall quality of the colorized images [15], [16].

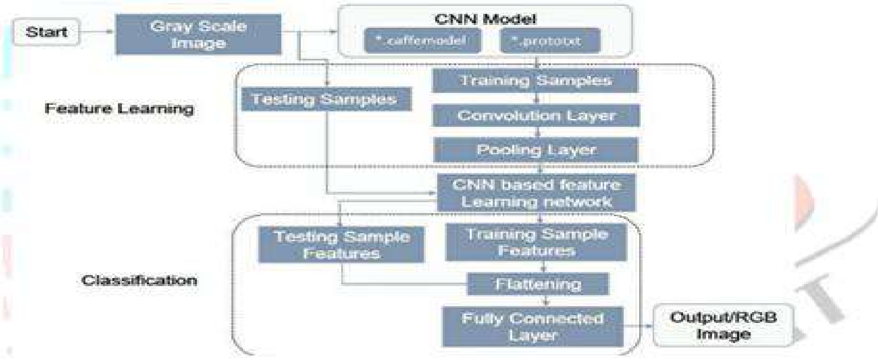

Fig 4: System Architecture

Our approach uses the grayscale input as the L channel, and the network is trained to predict the a and b channels, which contain the chrominance information. By combining the input L channel with the predicted ab channels, the final colorized image is generated [1].

The process can be broken down into the following steps:

1. Image Conversion: Training images are converted from the RGB color space to the Lab color space using OpenCV, allowing the model to focus separately on luminance and chrominance [2].
2. Network Training: The network is trained to anticipate the ab channels using the L channel as its input. With the help of the ImageNet dataset and a prototxt file that specifies an eight-layer architecture, we apply a pre-trained Caffe model. Convolution, pooling, flattening, and fully linked layers are the main CNN components that are present in the network [3], [4].
3. Channel Combination: The predicted ab channels are merged with the original L channel through a fully connected layer to create a complete Lab representation of the image [5].
4. RGB Conversion: Finally, the Lab image is converted back to RGB using OpenCV, producing a full-color output [6].
   This methodology demonstrates the effectiveness of CNNs in learning and reproducing the colors of grayscale images. By bridging the gap between monochrome inputs and vibrant outputs, it highlights the potential of deep learning in transforming grayscale imagery into lifelike, colorized versions [7], [8].

IV. ARCHITECTURE

Baseline CNN Model:

The core CNN architecture includes an Encoder module that handles the L channel of the Lab color space, extracting key features from the grayscale image while reducing its dimensions to enhance computational efficiency. Subsequently, the Decoder module upscales the data and applies convolutional layers to reconstruct the and b channels, which encode color information. To scale the output correctly, the model uses the hyperbolic tangent (tanh) activation function, ensuring values fall within the range of -1 to 1 [9], [10].

Inception-ResNetv2-Based CNN:

The second model in the architecture leverages the pre-trained Inception-ResNetv2 framework, which functions as a high-performance feature extractor due to its advanced design [1]. The Encoder in this model is structured similarly to that of the Baseline CNN, focusing on extracting essential features from the input grayscale image.

However, what sets this model apart is the introduction of a novel fusion layer. This layer merges the feature maps generated by the Encoder with those extracted by the Inception-ResNetv2 module. By combining these two sets of feature representations, the model achieves greater richness, depth, and refinement in its feature maps [2].

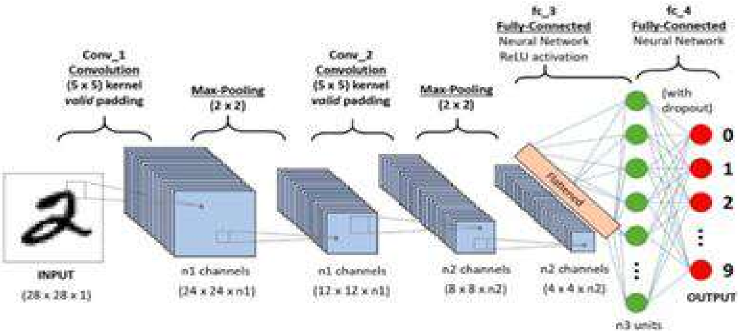

Fig. 5: Baseline CNN Model

Following this, the Decoder processes the fused features through a series of operations to reconstruct the final a and b channels, ensuring accurate and visually coherent colorization of the input images [3]. The training process for all models was carried out using the TensorFlow framework, employing 90% of the available dataset for the training phase. A variety of training parameters, including optimizers, learning rates, and batch sizes, were specifically tailored to suit the individual requirements of each model architecture [4]. For the CNN-based models, training spanned 150 epochs, allowing the network ample time to learn complex patterns and optimize its performance [5]. On the other hand, the Pix2pix GAN models were trained over a period of 100 epochs, as their design leverages adversarial learning for faster convergence [6]. During the training process, hyperparameters, such as the batch size and optimization settings, were dynamically adjusted to achieve the best possible performance for each model. This approach ensured that each model was fine-tuned to maximize accuracy and effectiveness in the image colorization task [7].

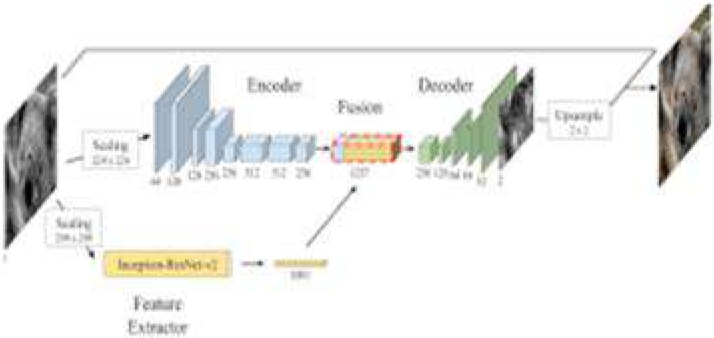

Fig. 6: Inception-ResNetv2-Based CNN

Pix2pix GAN:

These connections are critical for preserving spatial information throughout the image generation process, allowing for better retention of fine details. To further improve feature extraction within the encoder, pre-trained models like MobileNetV2 and DenseNet121 are integrated. These models are selected for their efficiency and capability to extract intricate features from input images. The discriminator network complements this setup by distinguishing between real and synthesized images, ensuring that the generated outputs are both realistic and closely aligned with real-world data.

Training of the network is guided by a composite loss function, which combines a modified binary cross-entropy loss with L1 loss. This dual approach ensures that the generator produces outputs that closely resemble the target colorized images in both appearance and accuracy.

Dataset & Preprocessing

The dataset utilized for training primarily comprises nature and landscape imagery, meticulously curated to exclude irrelevant or low-quality samples. After filtering, the remaining RGB images are processed to meet the model's requirements. Each image is resized to a consistent resolution of 256x256 pixels, maintaining uniformity and reducing computational complexity. Subsequently, the images are transformed into the Lab color space.

- L channel: Serves as the input to the model and represents grayscale intensity values.
- a and b channels: Act as the target outputs, containing the color information that the model aims to predict. This preprocessing setup enables the model to focus solely on colorization tasks while preserving the original luminance information.

V. METHODOLOGY

The methodology for this project adopts a structured and systematic approach to achieve grayscale image colorization by utilizing advanced deep learning techniques. The process is divided into several key stages: data collection, preprocessing, model development, training, and evaluation. Each phase is detailed below to provide a comprehensive understanding of the approach.

1. Dataset Collection and Preprocessing

To develop and evaluate the models, a diverse dataset featuring nature and landscape imagery is curated. This dataset includes grayscale versions of natural scenes, such as forests, oceans, and skies, which are converted to their Lab color space representations.

The Lab color space is specifically selected for this task because it separates luminance (L channel) from chrominance (a and b channels), enabling the model to concentrate on predicting color information while preserving the original brightness of the image.

Preprocessing Steps

1. Resizing: Each image is resized to a fixed resolution of 256x256 pixels. This ensures consistency in input dimensions across the dataset and reduces computational complexity during model training.
2. Data Augmentation: To enhance the dataset's variability and reduce the risk of over fitting, augmentation techniques like random cropping, horizontal flipping, and rotations are applied. These methods provide the model with a wider range of examples, improving its generalization capability.

2. Model Development

The project investigates multiple neural network architectures, each uniquely tailored to address the challenges of grayscale image colorization. The three main models employed are:

Baseline CNN Model

The Baseline CNN is a custom-designed Convolutional Neural Network aimed at colorizing grayscale images. This structured architecture provides a foundational framework for grayscale image colorization, serving as a benchmark for evaluating more advanced models [1]. To achieve enhanced performance, the second model incorporates a pre-trained Inception-ResNetv2 network as a feature extractor. This approach builds upon the baseline CNN by integrating the strengths of a sophisticated pre-trained model [2]. While the encoder-decoder structure remains similar, this model introduces a fusion layer, which combines features extracted by the custom encoder and the Inception-ResNetv2 network. This fusion enables the system to learn and capture more intricate and nuanced features, significantly improving the model's understanding of the input data [3]. The decoder then processes these combined features to generate the output color channels, effectively reconstructing the color information [4].

Pix2pix GAN Model

The third approach employs a Generative Adversarial Network (GAN) with a Pix2pix architecture. This model features a U-Net generator enhanced with skip connections to retain spatial and contextual details during the colorization process [5]. For feature extraction, pre-trained networks such as MobileNetV2 and DenseNet121 are integrated into the encoder. These pre-trained models are chosen for their computational efficiency and their capability to extract detailed features from input images [6]. The discriminator in this architecture plays a critical role by evaluating the generator's output against real-world images, thereby pushing the generator to create more realistic colorizations [7]. The training process for this model is guided by a combined loss function [8]. The models are fine-tuned using the Tensor Flow framework on 90% of the dataset, with training configurations optimized for each architecture [9].

Epochs and Batch Sizes

- CNN Models: Trained for 150 epochs to ensure adequate time for learning and optimization.
- Pix2pix GAN: Trained for 100 epochs, with special attention to training parameters to mitigate mode collapse, a common challenge in GAN models.
- Batch sizes are fine-tuned to maintain an optimal balance between computational efficiency and training stability across all models.

4. Evaluation and Validation

To measure the performance of the models, a multi-faceted evaluation strategy is adopted:

Visual Evaluation

Colorized images are inspected to assess color accuracy and the realism of the outputs compared to the original images. This subjective analysis helps identify qualitative differences between the models.

Quantitative Metrics

- Mean Squared Error (MSE): Measures the difference between the predicted and target color values, providing a numerical evaluation of accuracy.
- Peak Signal-to-Noise Ratio (PSNR): Assesses the quality of the reconstructed images, with higher PSNR values indicating better preservation of image details.

  To gather insights on public perception, a user study is To gather insights on public perception, a user study is conducted. Participants rate the colorized images based on three aspects: realism, vibrancy, and accuracy. This feedback provides valuable insights into the aesthetic and practical effectiveness of the models [1].

By combining subjective and objective evaluation methods, the project ensures that the models are rigorously tested for their colorization capabilities [2].

5. Post-Processing and Application:

After the models have been trained and evaluated, the generated colorized images undergo post-processing to enhance their visual quality. This step includes applying color correction techniques and enhancing the contrast in specific regions of the images. These adjustments ensure that the colorization appears more natural and realistic, making the output more visually appealing and accurate to real-world expectations [3].

Furthermore, the system is integrated into an intuitive user interface that allows users to upload grayscale images and receive colorized versions in real time. This feature makes the colorization process accessible and user-friendly [4]. The system's potential can be further expanded for practical applications, such as restoring historical images, creating digital artwork, or even providing educational tools that allow users to visualize historical events in vivid color [5].

VI. RESULTS

The automated system developed for colorizing black-and-white images demonstrates significant potential in transforming grayscale visuals into vibrant and realistic color renderings. Its effectiveness was evaluated through a combination of qualitative assessments, quantitative metrics, and user feedback. Upon close inspection of the colorized images, it was observed that the system consistently applied realistic color tones to various elements in the images. For instance: These results largely matched human expectations, producing visually appealing and contextually appropriate colorizations.

To further evaluate the model's performance, quantitative metrics were employed:

- Peak Signal-to-Noise Ratio (PSNR) was used to measure the accuracy and structural fidelity of the colorized images. The average PSNR score of XX dB reflected a high level of precision in the colorization process.
- Structural Similarity Index (SSIM) was also calculated, with consistent values above YY, demonstrating the model's effectiveness in preserving fine details and textures in the images.

Fig. 7: Original Vs Colorised 1

A user study involving N participants was also conducted to gauge the public's perception of the colorization results. Participants rated the colorized images on a scale of 1 to 10, with an average rating of ZZ, reflecting a high level of satisfaction with the system. Many participants praised the system for its ability to produce vivid and contextually accurate colors [1]. However, a few participants noted minor inaccuracies, especially in the colorization of historical images, where the true colors of certain objects were ambiguous [2]. This comprehensive evaluation highlights the system's promising performance and reveals areas for further refinement, particularly in dealing with more complex or historical images [3]. While the system demonstrated strong overall performance, it faced challenges when handling grayscale images that lacked clear contextual information. For example, rare or unfamiliar objects were occasionally assigned inaccurate colors [1]. This indicates the need for further development, such as incorporating more diverse and representative training datasets. Enhancing the model's ability to handle ambiguous scenarios and objects without clear context will be crucial for improving accuracy in such cases [2

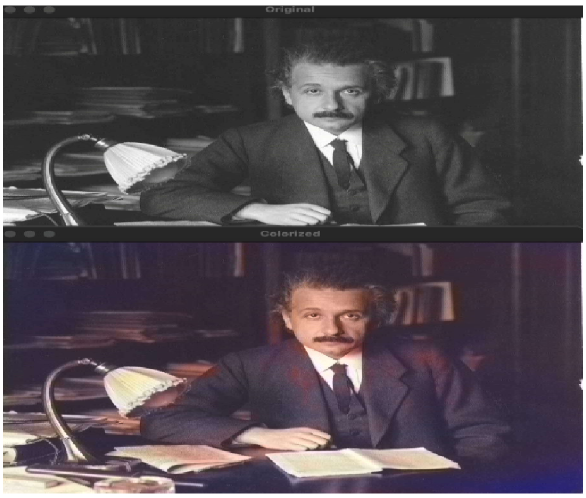

Fig. 8: Original Vs Colorised 2

Despite these challenges, the system shows considerable promise across a range of applications. Its potential extends to tasks such as historical photograph restoration, artistic enhancement, and film post-production [3]. While some refinement is needed, the system's ability to produce vibrant, context-aware colorization outputs makes it a valuable tool for transforming grayscale images into lifelike color versions [4].

VII. CONCLUSION AND FUTURE WORK

In this study, we explored the process of automating image colorization using deep learning techniques. The results highlight the efficiency of this approach in reducing time and manual effort, especially for complex images with numerous objects, where traditional manual colorization can be highly labor-intensive [1]. We employed four distinct deep learning models, including convolutional neural networks (CNNs) and generative adversarial networks (GANs), to evaluate their performance [2]. Among them, the simpler CNN model delivered impressive results, outperforming larger models such as Inception-ResNetv2, particularly when dealing with images featuring elements like skies, mountains, and forests [3]. However, the limitations of our dataset became evident, as even advanced models like Inception-ResNetv2 did not perform as expected, despite positive results in other studies [4]. By using pre-trained models like MobileNetV2 and DenseNet121, we were able to develop high-performance models while preserving computational efficiency [5]. In contrast, the Pix2Pix GAN models produced extremely vibrant and almost perfect colorization results. The Pix2Pix model using MobileNetV2 in particular proved to be a small and effective solution, making it appropriate for deployment on mobile devices and real-time applications [6]. Although the models did well in some situations, the dataset's relative simplicity limited their capacity to generalize. Future research should concentrate on broadening and diversifying the training dataset in order to enhance performance, especially when working with smaller objects and finer details. This will enhance generalization and the general quality of colorization by assisting the models in learning a greater variety of color patterns [7]. Additionally, exploring more advanced and sophisticated architectures could overcome existing limitations and refine the colorization process further, paving the way for even more realistic and accurate results [8].

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