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**PROJECT TITLE :**

**IMAGE COLORIZATION, FROM BLACK  
AND WHITE TO COLOR, USING SELF  
SUPERVISED DEEP LEARNING MODELS**

**P R E S E N T A T I O N B Y :**

**SAYAN ROY**

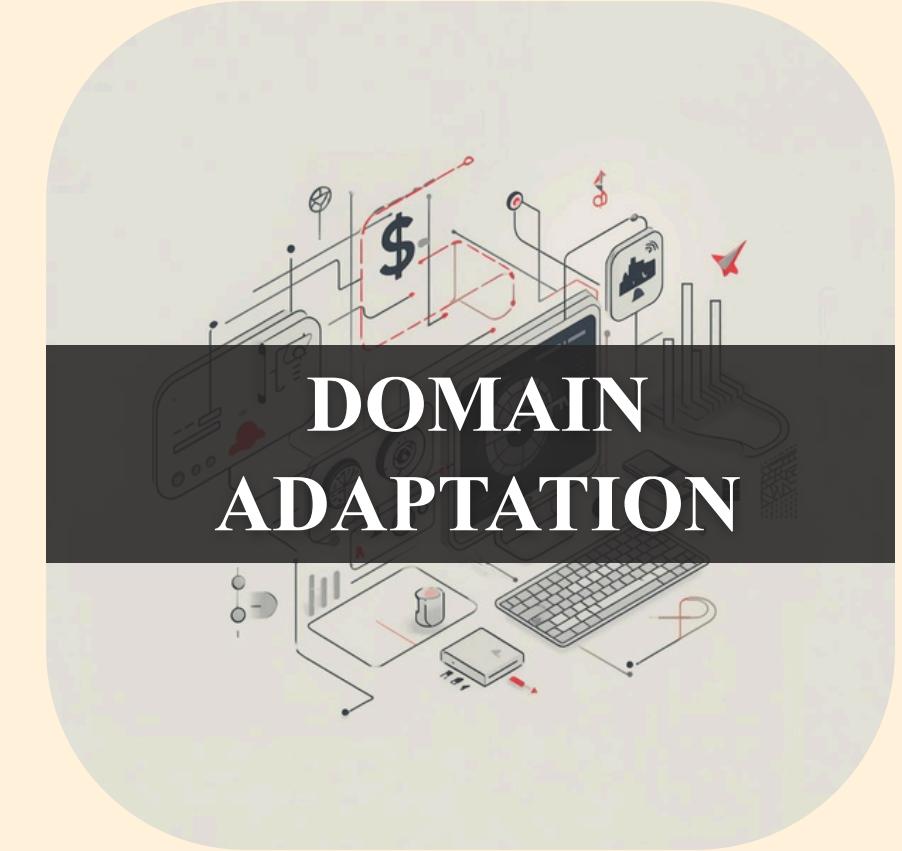
# Problem & Motivation: Why Colorize?



Bring historical photos to life,  
preserving memories with  
added visual context and  
emotional depth.

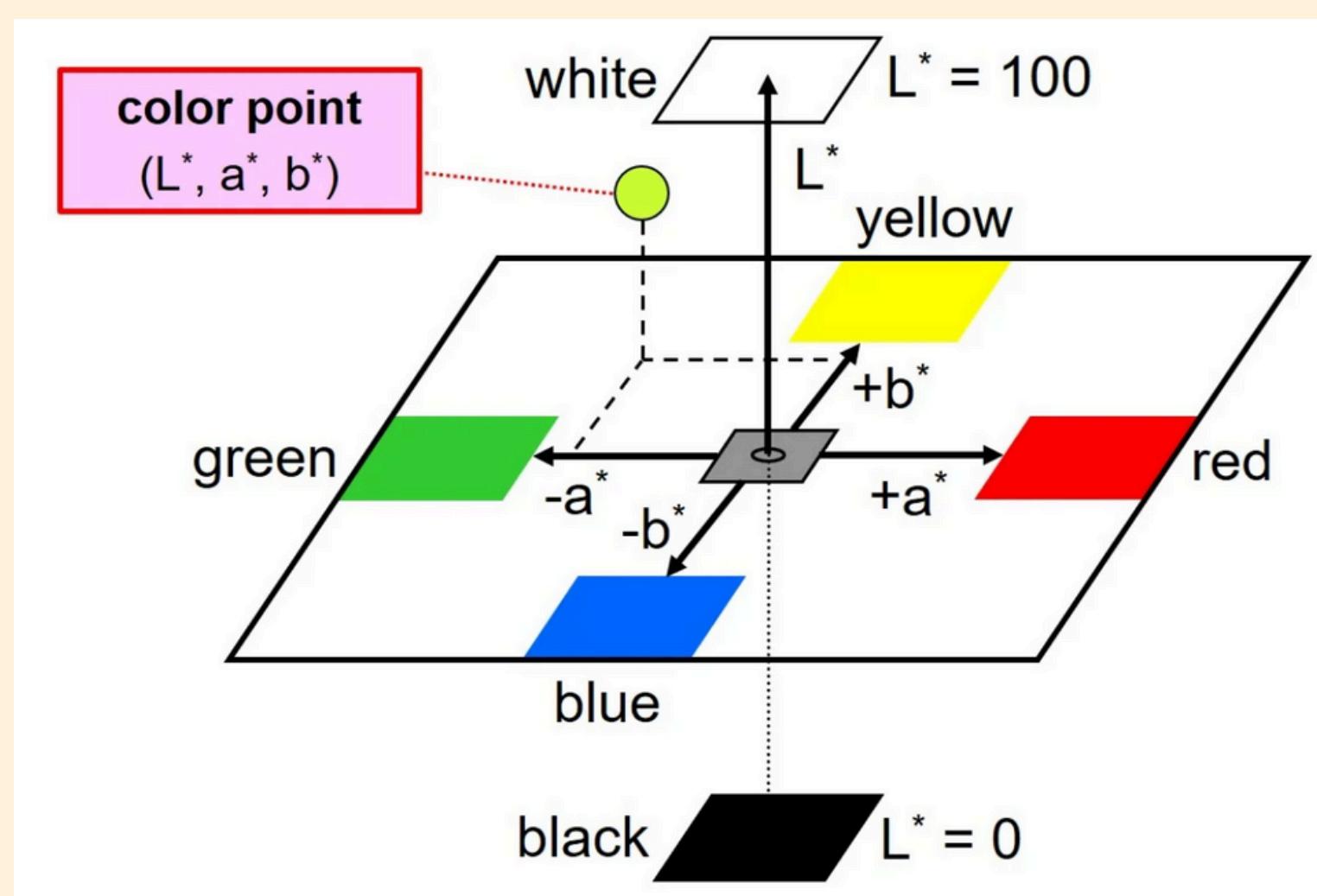


Empower artists and designers  
with tools for rapid  
prototyping and style transfer  
in various media.



Enhance datasets for  
downstream computer vision  
tasks where color information is  
beneficial but scarce

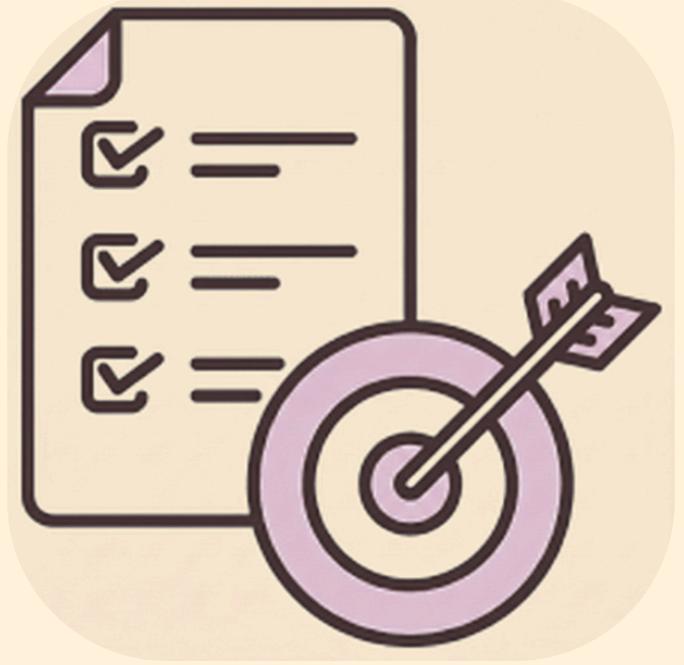
# LAB Colour Space



## What is LAB color space?

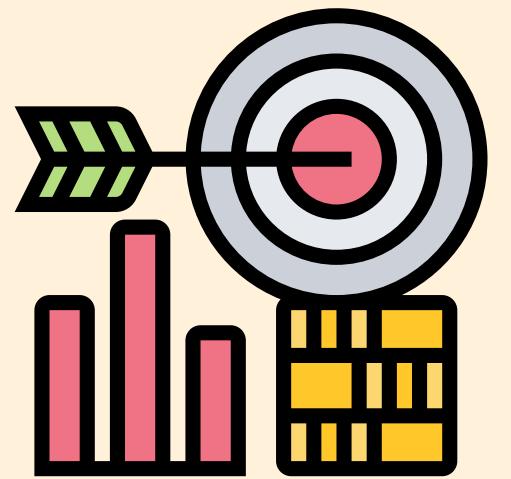
LAB color space is a three-dimensional color model that includes three components:

- $L^*$ : Represents lightness, ranging from 0 (black) to 100 (white).
- $a^*$ : Represents the green-red axis, where negative values indicate green and positive values indicate red.
- $b^*$ : Represents the blue-yellow axis, with negative values indicating blue and positive values indicating yellow



# OBJECTIVE

Train a model without manual labels to recover plausible color (a and b) from grayscale L channel input.



# Main Challenges in Colorization

## Ambiguous Color Priors

A single grayscale pixel can correspond to many possible colors.

## High-Frequency Detail

Maintaining sharp edges and textures while applying color.

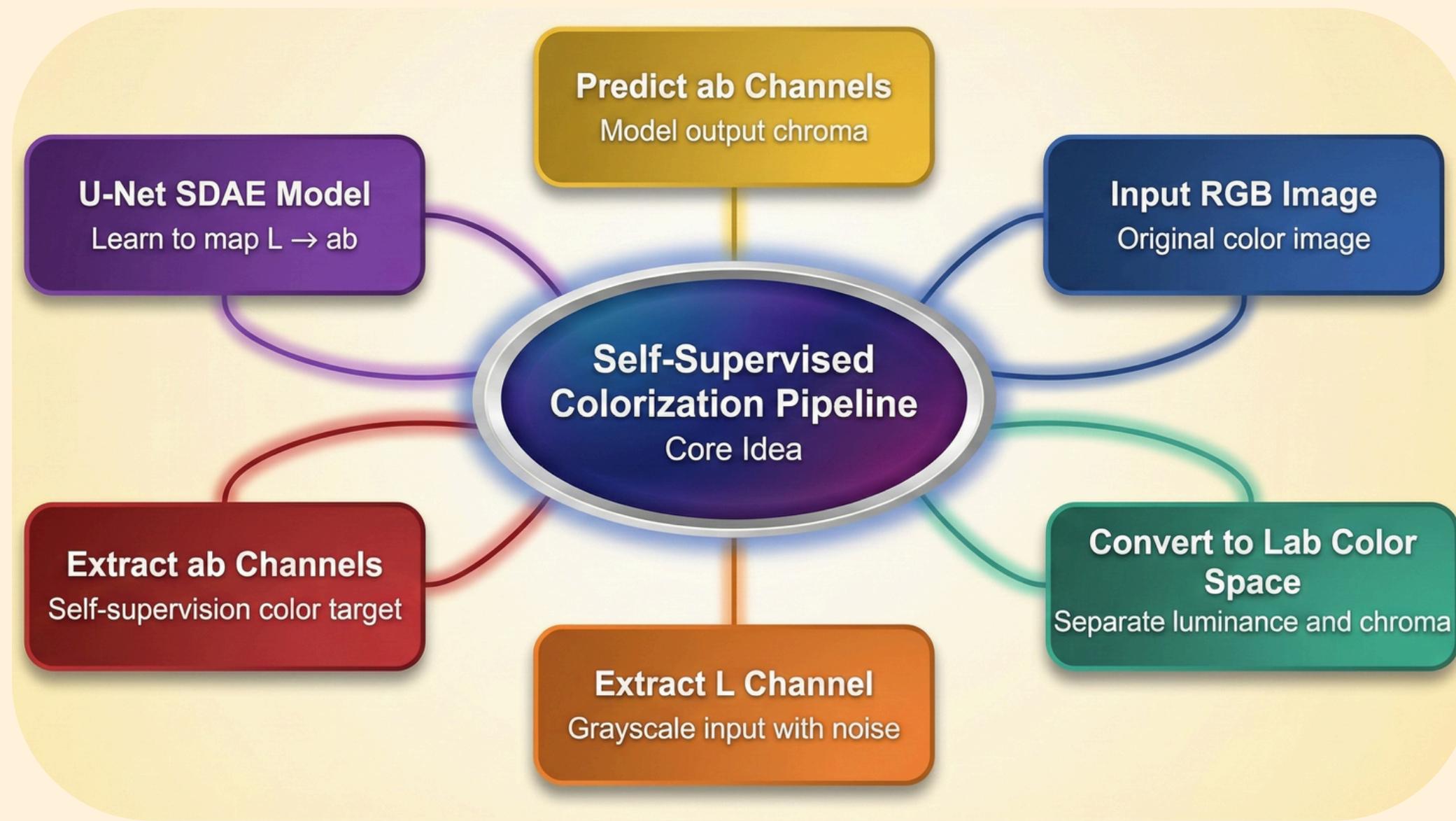
## Color Bleeding

Preventing color from spreading into unintended regions.

## Metric Mismatch

Standard metrics (PSNR, SSIM) often fail to capture perceptual quality.

# Core Idea: Self-Supervised Method Overview



- **Input-Target Split** : Automatically decomposes RGB images into grayscale (L) inputs and chromatic (ab) targets
- **Denoising Strategy** : Injects Gaussian noise to drive restorative generation, ensuring robust feature extraction over simple pixel memorization.
- **U-Net Architecture** : Leverages an SDAE with skip connections to preserve high-frequency spatial details for precise edge alignment.

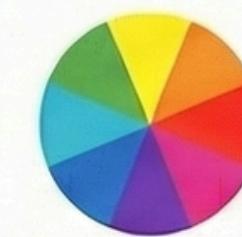
# Dataset & Preprocessing

## 1. Dataset: Stable ImageNet-1K Subset



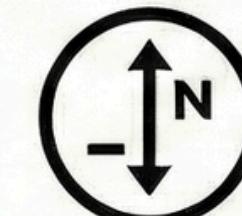
- Stratified Subset for Class Diversity
- Balanced Train/Val Split

## 2. Color Space & Preprocessing



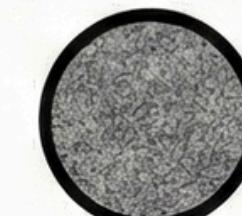
### RGB → CIELAB Conversion

Separate L (Luminance)  
& ab (Chrominance)



### Normalization: L & ab to [-1, 1]

$$\begin{aligned} L_{\text{norm}} &= (L/50) - 1; \\ ab_{\text{norm}} &= ab/128 \end{aligned}$$

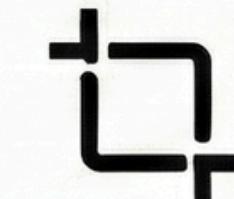


### Self-Supervised Augmentation

Inject Gaussian Noise into  
L Channel

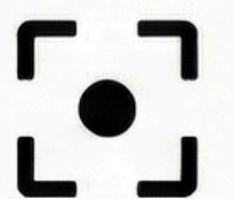
$$L_{\text{noisy}} = L + \text{noise} * \text{std}$$

## 3. Transformations (Train & Val)



### Training: Random Resized Crop

Scale & Positional  
Invariance



### Validation: Center Crop

Consistent  
Evaluation

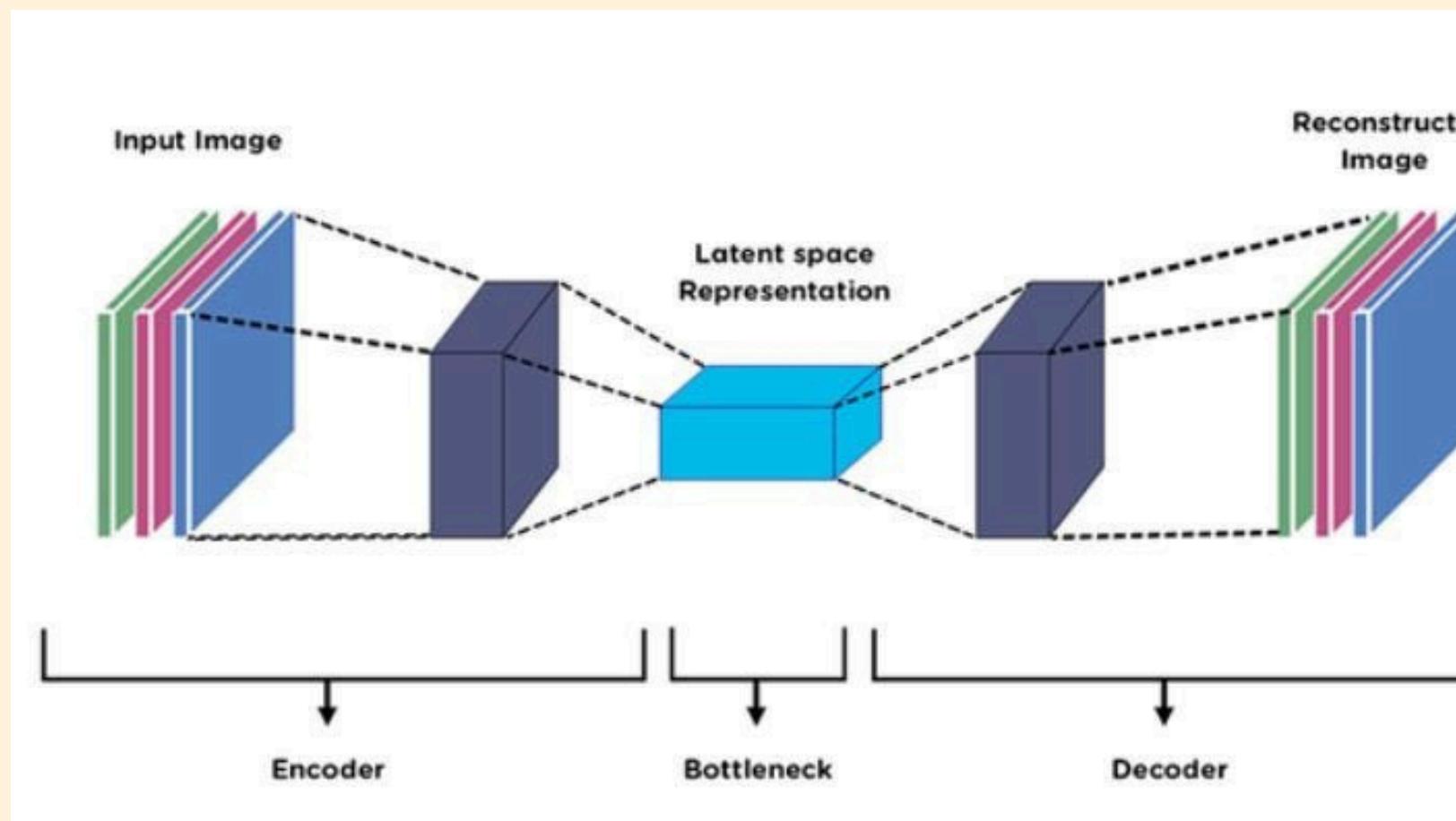
### Model Input: Noisy L Channel

### Ground Truth Target: ab Channels

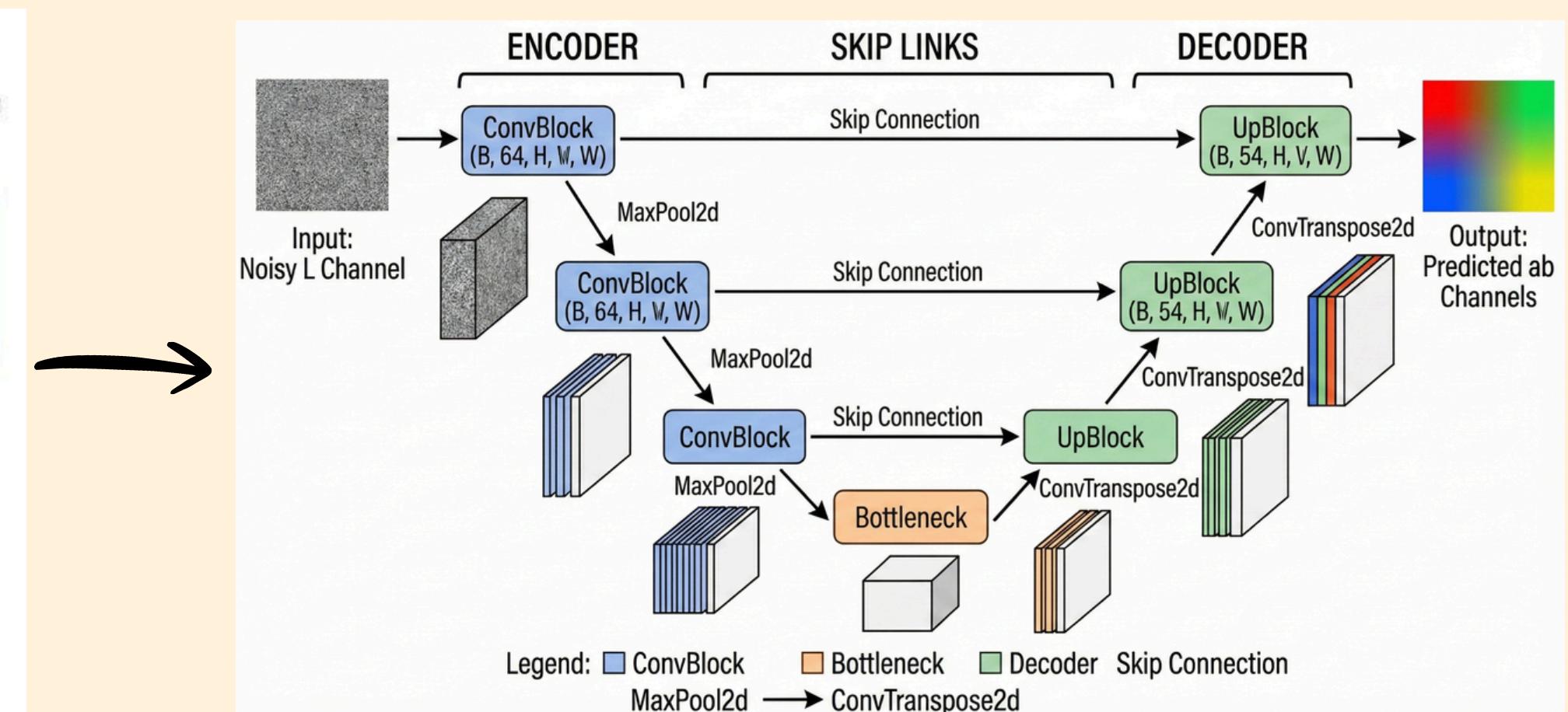
# Model Architecture: U-Net SDAE

- Our model, a U-Net adapted as a **Self-Denoising Autoencoder (SDAE)**, predicts ‘ab’ color channels from a noisy ‘L’ input.
- **Key features:** captures high-level semantic information and fine-grained spatial details.

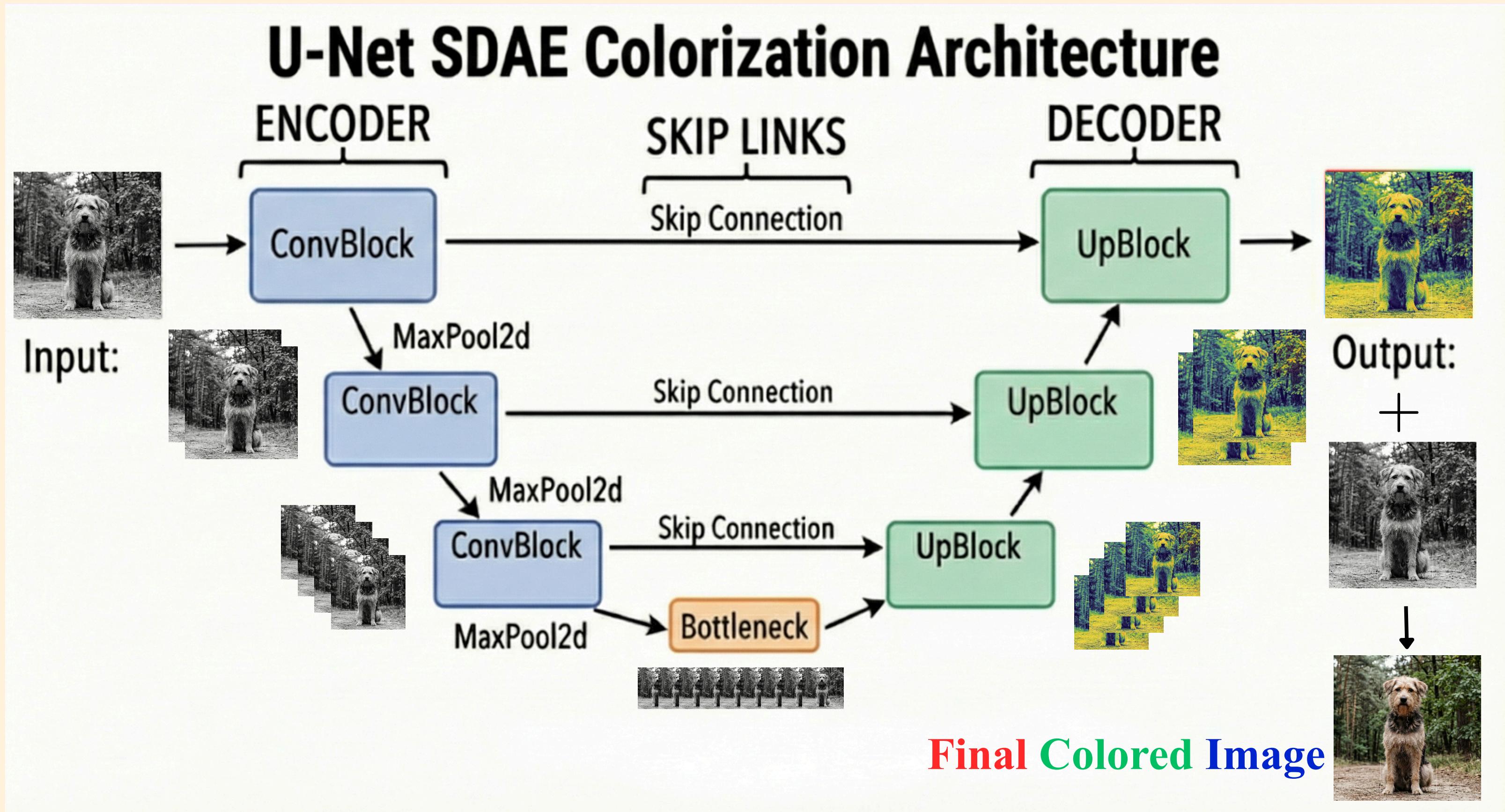
## 1. Basic Encoder-Decoder Concept



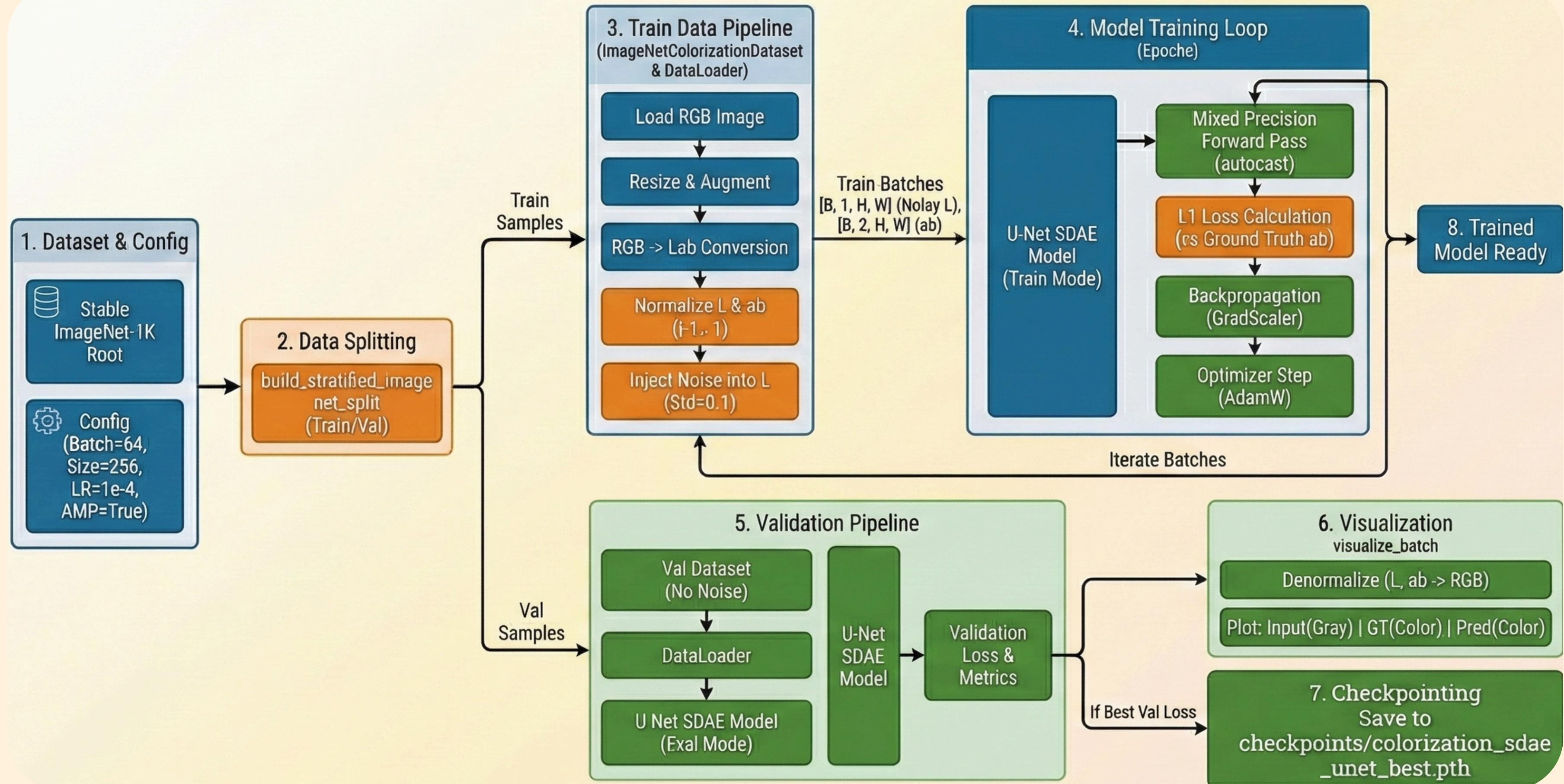
## 2. Our U-Net SDAE Colorization Architecture



# Visualization of the Model's Working



# End to End System Training Pipeline



# Results & Visualizations

## Quantitative Evaluation: Visual Results (After only 30+ epochs)



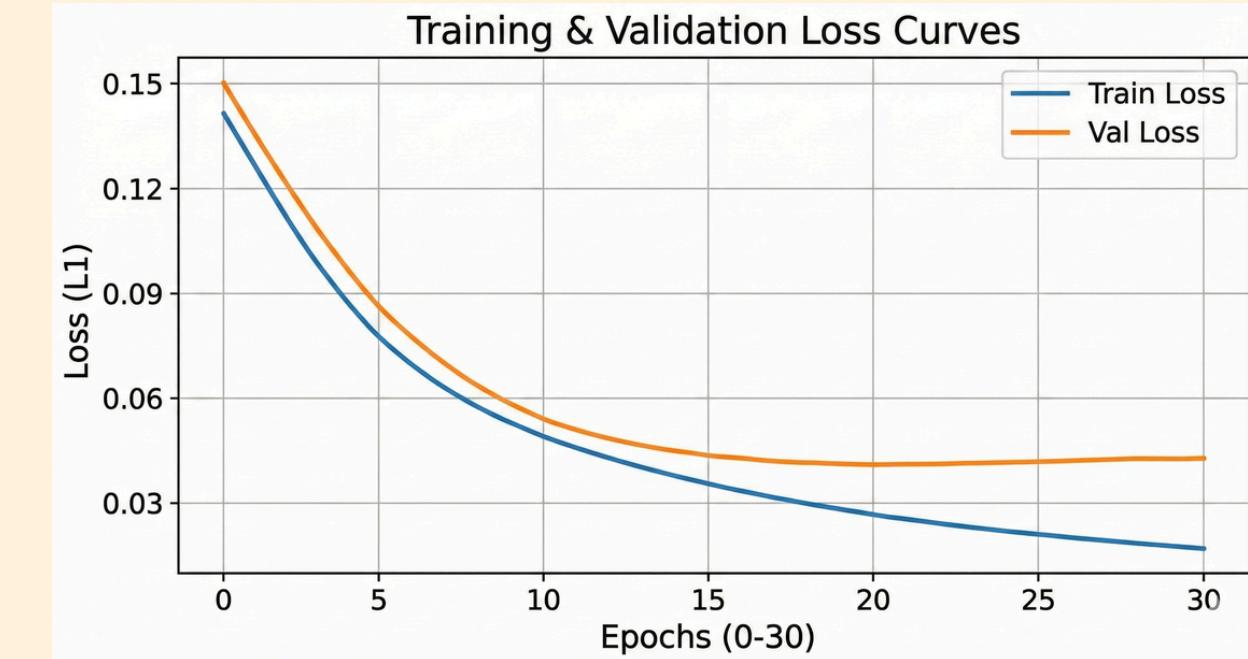
Model successfully distinguishes semantic regions ( e.g. **red berry vs green stem** ) and preserves high-frequency details, independent of gray scale intensity

## Quantitative Metrics & Training Dynamics

### Key Performance Metrics

Metric	Value	Interpretation
Final Validation L1 Loss	~0.04	Low pixel-level error
Peak Signal-to-Noise Ratio (PSNR)	~26.0 dB	High reconstruction quality

*Note: Metrics indicate strong alignment with ground truth.*



### Analysis & Limitations:

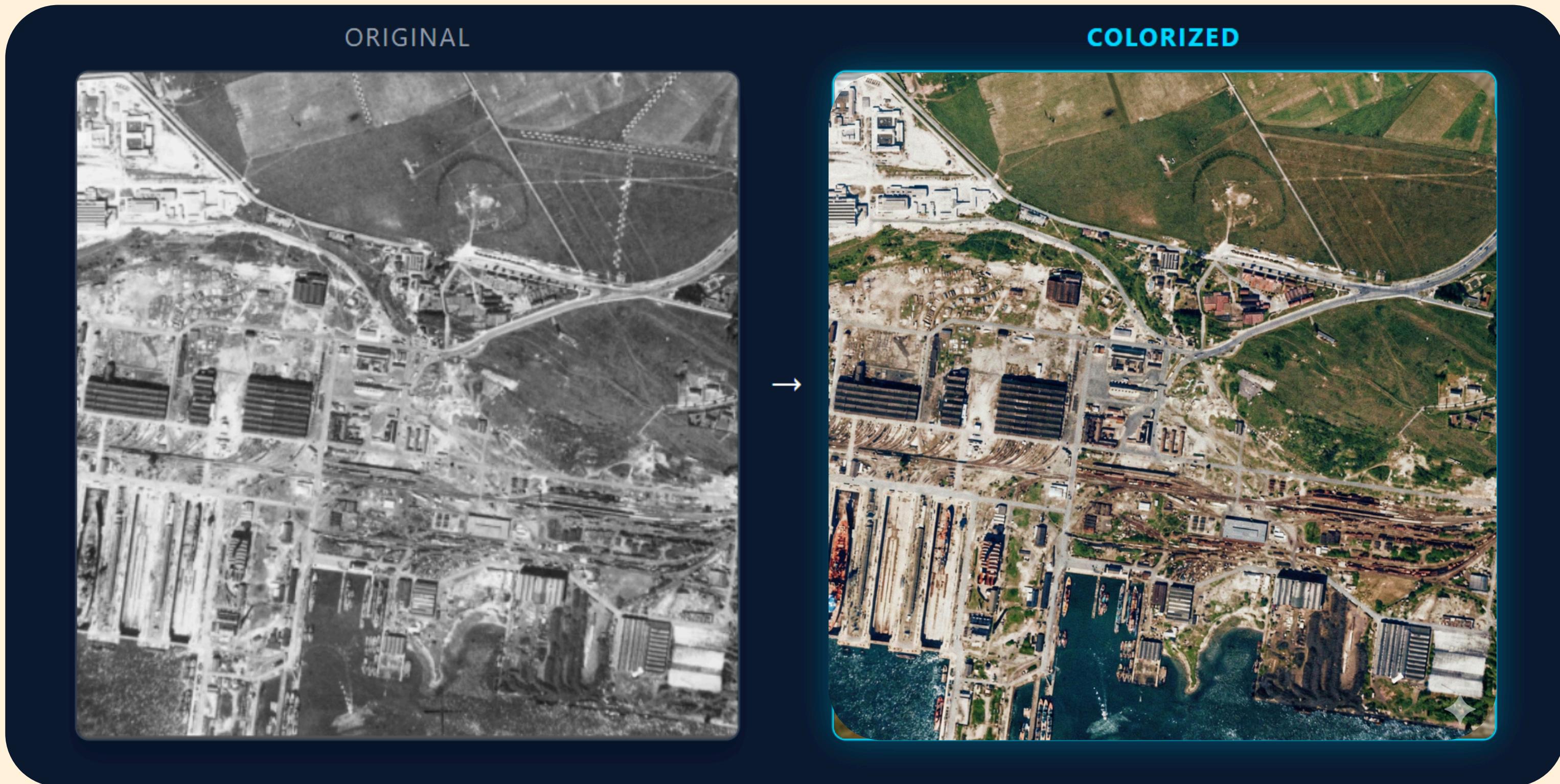
- Stable Convergence:** SDAE approach (noise injection) acts as an effective regularizer, preventing overfitting.
- Color Ambiguity:** Model may predict desaturated tones in ambiguous, untextured areas to minimize L1 error.
- L1 Loss Trade-off:** Slight ‘averaging’ effect can lead to less vibrant colors in complex scenes compared to ground truth.

# Real-World Application: Cultural Heritage Preservation

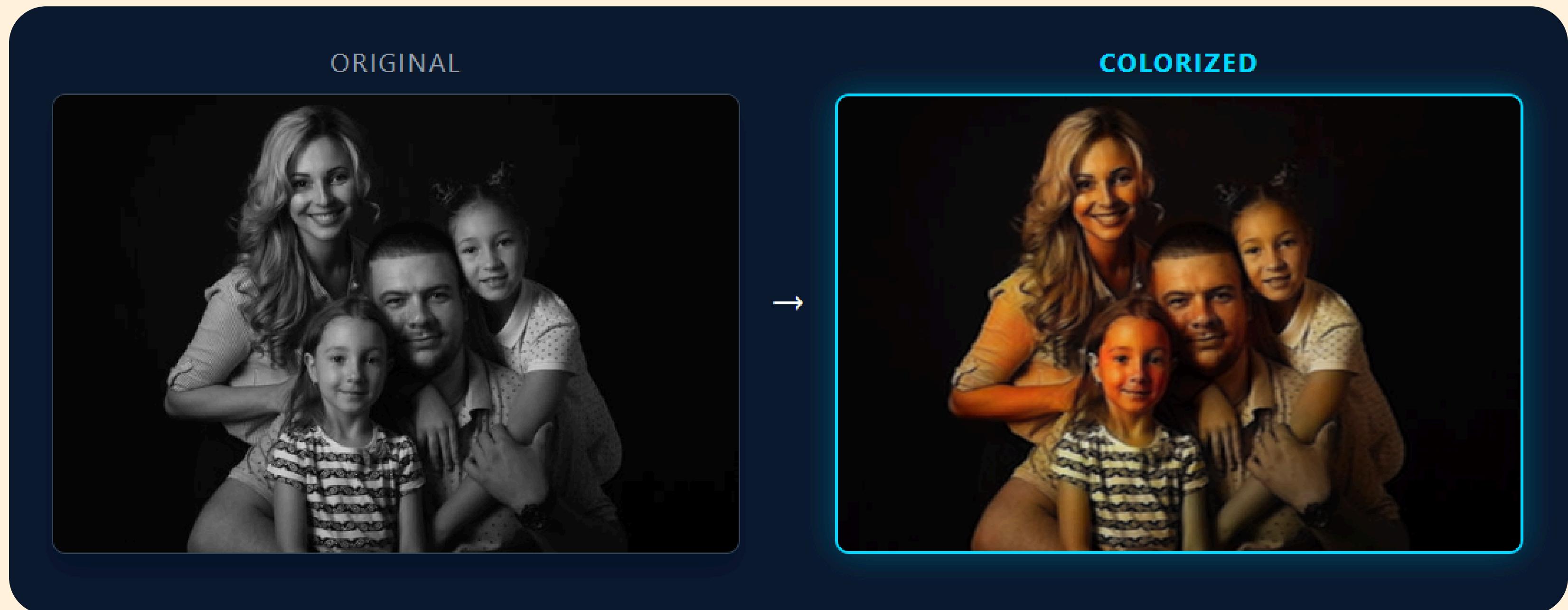
## Restoring Masterpieces: Satyajit Ray's Pather Panchali (1955)



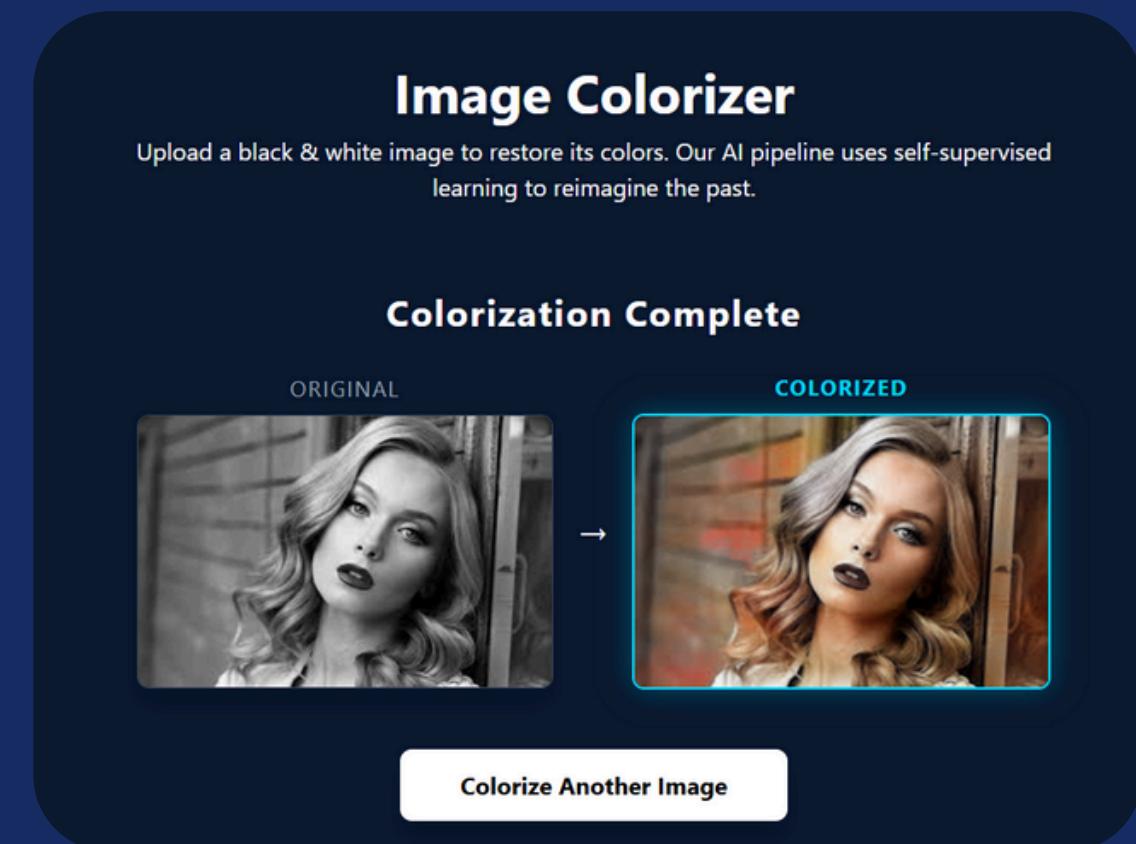
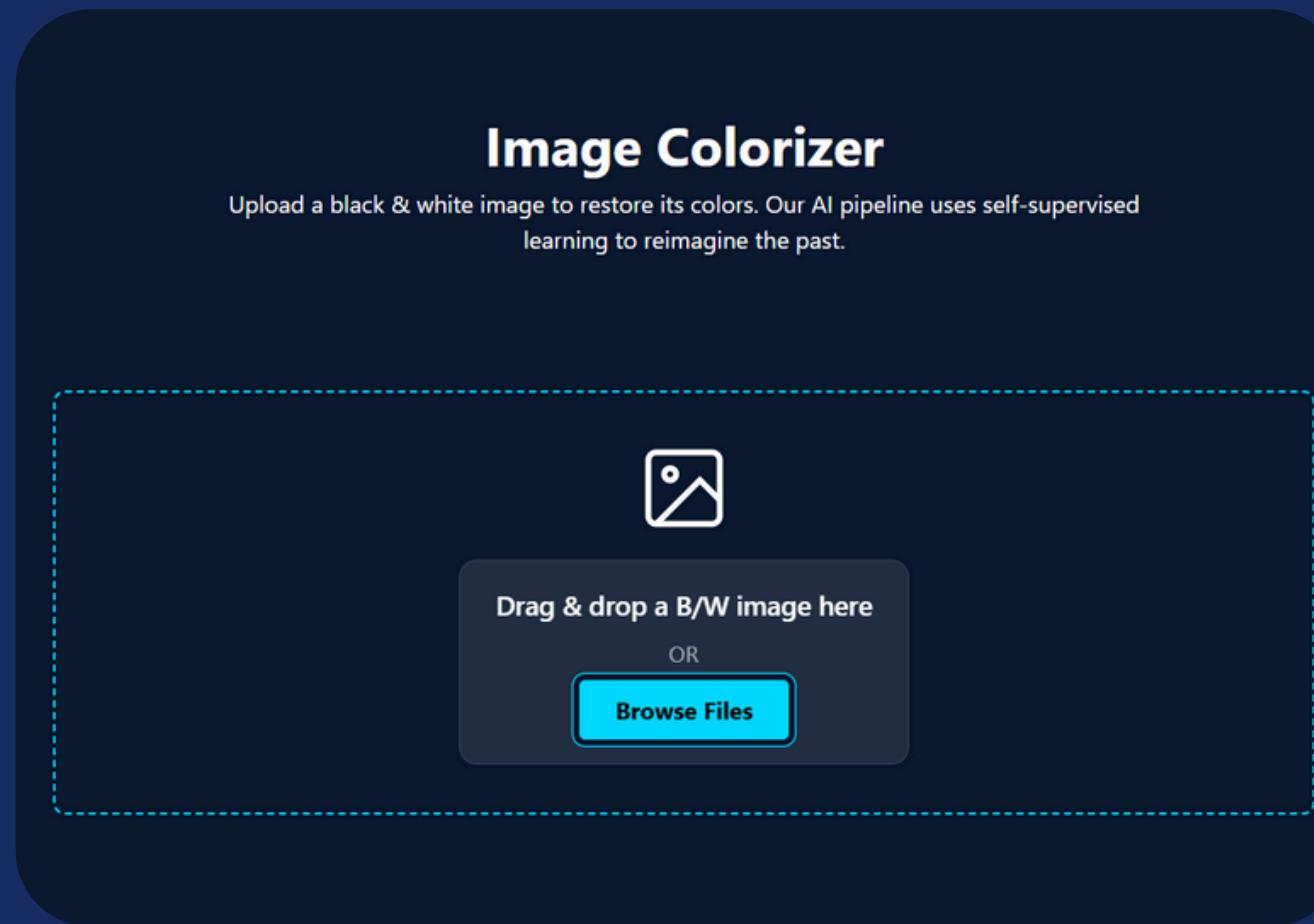
# Satellite & Aerial Imagery Enhancement (Gov + Industry)



# Consumer Apps (Family Photo Colorization)

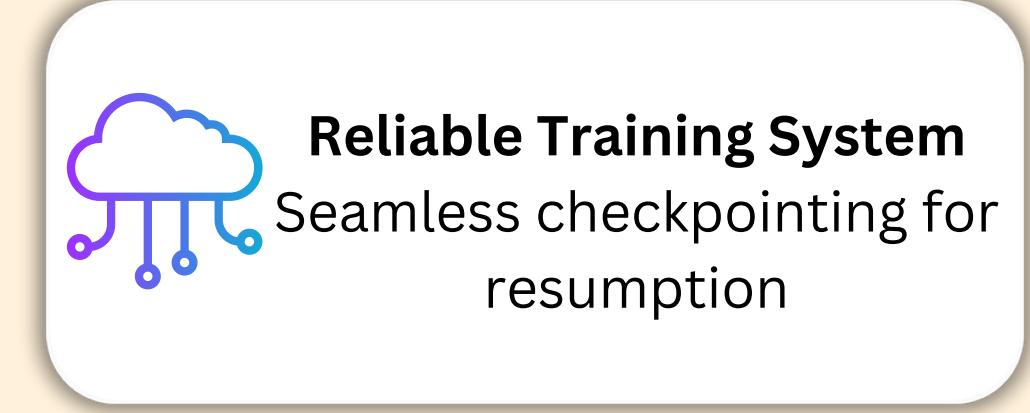
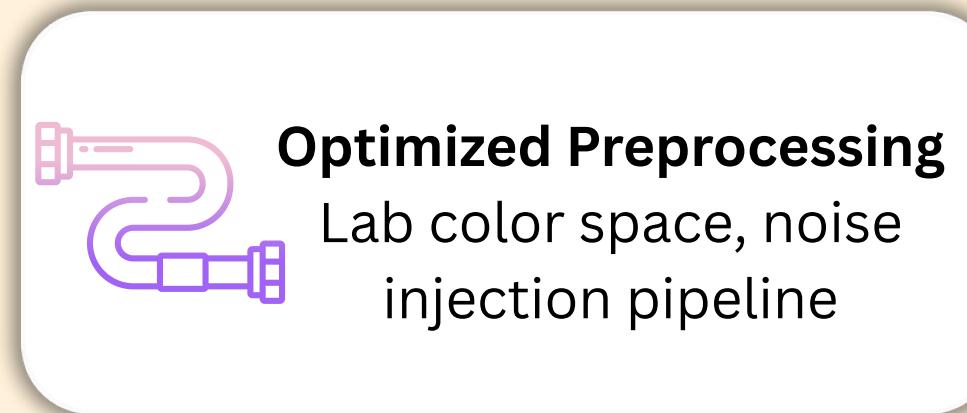
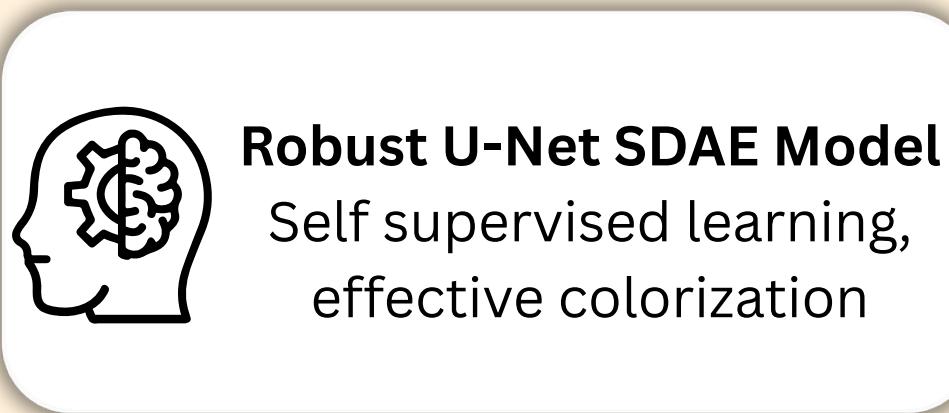


# User Interface



# Conclusion & Future Roadmap

## Key Achievements



## Future Enhancements & Next Steps



**Perceptual Losses**  
(VGG/GAN for visual realism)

**B&W Movie Restoration:**  
with temporal consistency

**High-Resolution Colorization pipeline**  
preserving fine details

**User-Guided Color Hints**  
(scribbles for artistic control)

**THANK YOU**