

# Emotion-Based Style Transfer

An Innovative ML Approach to Visual Emotion  
Recognition and Artistic Style Application

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# Background & Significance

Traditional image style transfer focuses on low-level features like textures and colors without considering emotional content. However, the core value of artistic works lies in their ability to evoke emotional responses.

## Key Insight:

Integrating emotional cognition into image style transfer creates artistic effects with greater emotional resonance and more personalized visual experiences.



# Problem Definition

01

How can we effectively map emotional states to corresponding visual representations?

02

Can we create an automated system for style transfer based on emotional context?



# Key Assumptions

## Emotion Quantification

Images can be analyzed to extract probability distributions across six basic emotions based on their visual characteristics including color, texture, composition, and other learnable features.

## Artwork Emotion Mapping

The emotional characteristics of artworks in the WikiArt dataset, derived from human subject interviews, can be represented as probability distributions across the same emotional dimensions.

## Emotional Correspondence

Visual style transfer between images with similar emotional distributions will result in more meaningful and resonant artistic transformations.





# System Architecture

Our emotion-based image style transfer system consists of three main components working in sequence to transform user-uploaded images into emotionally resonant artwork.



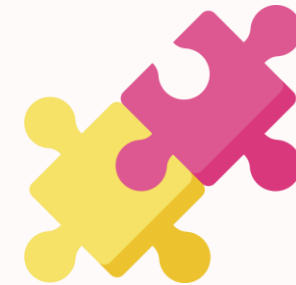
## Input Image

User-uploaded content



## Emotion Analyzer

Extracts emotion probabilities



## Similarity Matcher

Finds emotionally similar artwork



## Style Transfer

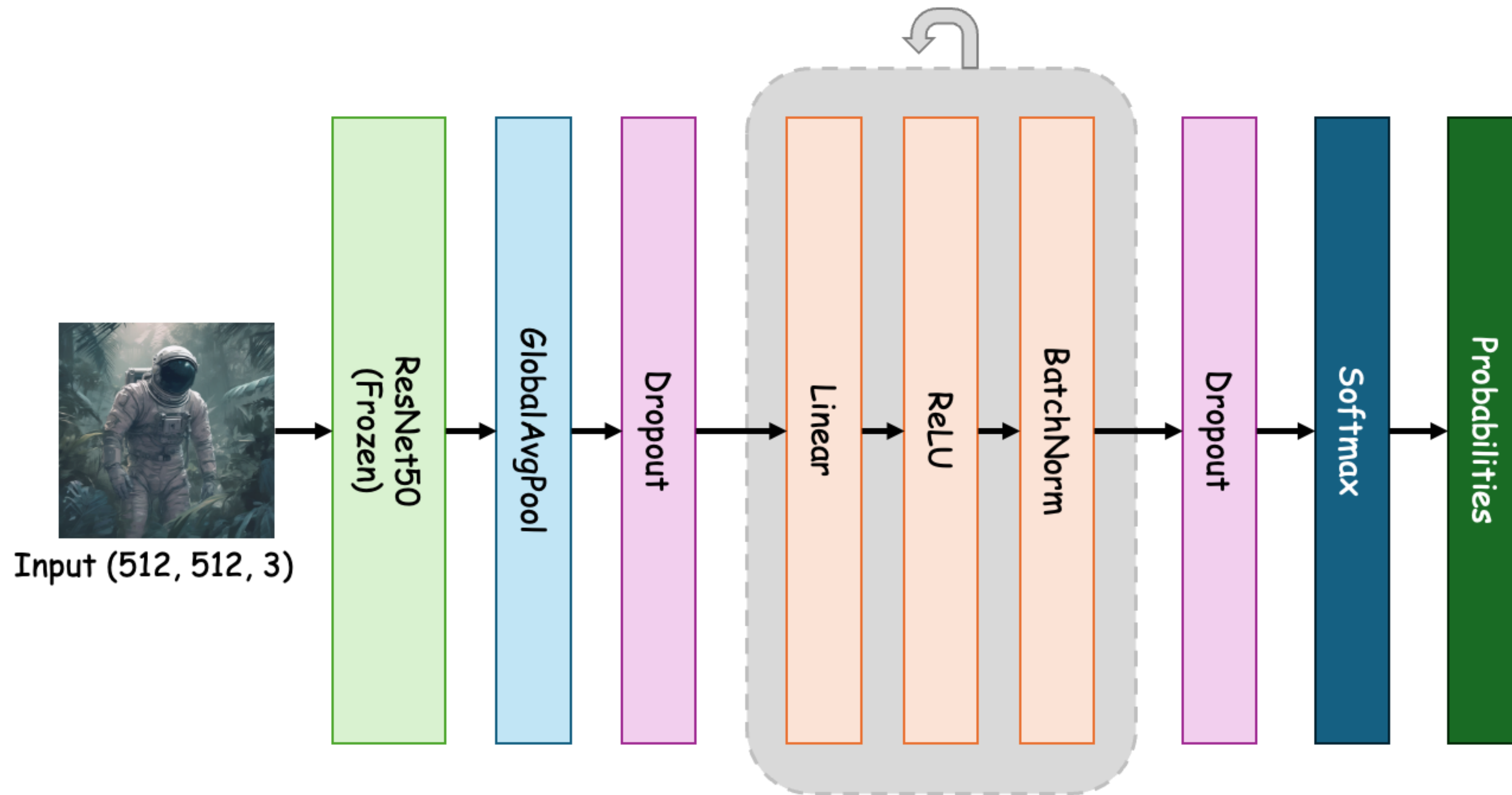
Generates stylized output



## Key Innovation:

Unlike traditional style transfer systems that focus solely on visual features, our approach creates a bridge between computational art generation and human emotional experience by considering the emotional congruence between content and style images.

# Emotion Analysis Model





# Training Strategy

## Dataset: Emotion6 (Chen, n.d.)

- ✓ 1980 images (330 per emotion category)
- ✓ Six basic emotions: anger, disgust, fear, joy, sadness, surprise
- ✓ Each image has dominant emotion and probability distribution

## Hybrid Loss Function

### KL Divergence Loss (0.7)

Optimizes probability distribution matching

+

### Cross-Entropy Loss (0.3)

Optimizes dominant emotion classification

*The hybrid approach balances distribution learning with accurate dominant emotion prediction*

## Data Augmentation

- ✓ Original images plus 30° rotated versions
- ✓ All images resized to 512×512 resolution
- ✓ Standard normalization for pretrained model compatibility



# Performance Results

|            | TRAINNING STRATEGY |         |                   |
|------------|--------------------|---------|-------------------|
|            | KL only            | CE only | Hybrid (selected) |
| TRAIN LOSS | 0.0653             | 0.5718  | <b>0.3582</b>     |
| VAL LOSS   | 0.1444             | 0.6633  | <b>0.4514</b>     |
| TRAIN ACC  | 0.7027             | 0.6692  | <b>0.7020</b>     |
| VAL ACC    | 0.5707             | 0.5808  | <b>0.5859</b>     |

## Key Finding:

The hybrid loss approach achieved the best balance between distribution learning and dominant emotion prediction. This is particularly important for our application, as the emotional matching system relies on accurate probability distributions rather than just dominant emotion classification.



# Emotion Analysis Model

Emotion Prediction Results

Image 1



Predicted: joy

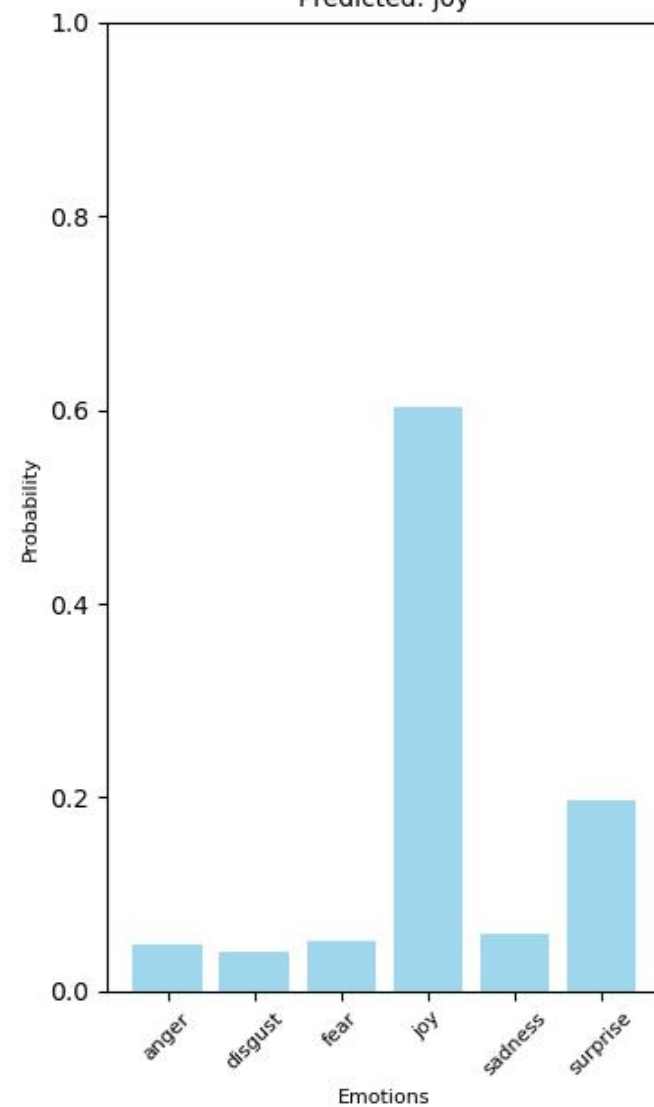


Image 2



Predicted: joy

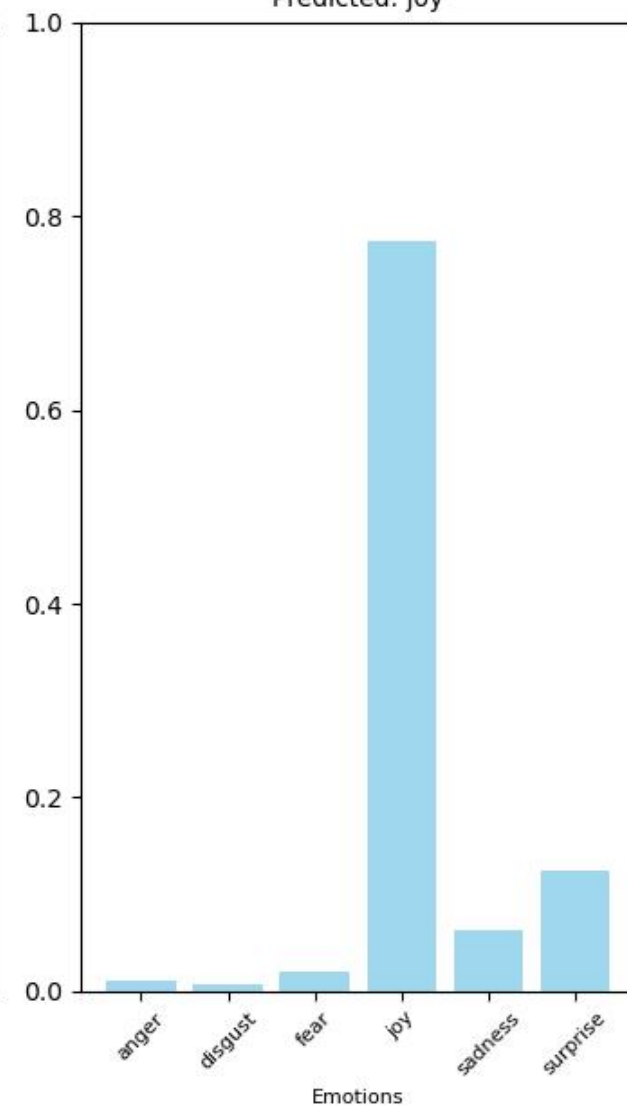


Image 3



Predicted: joy

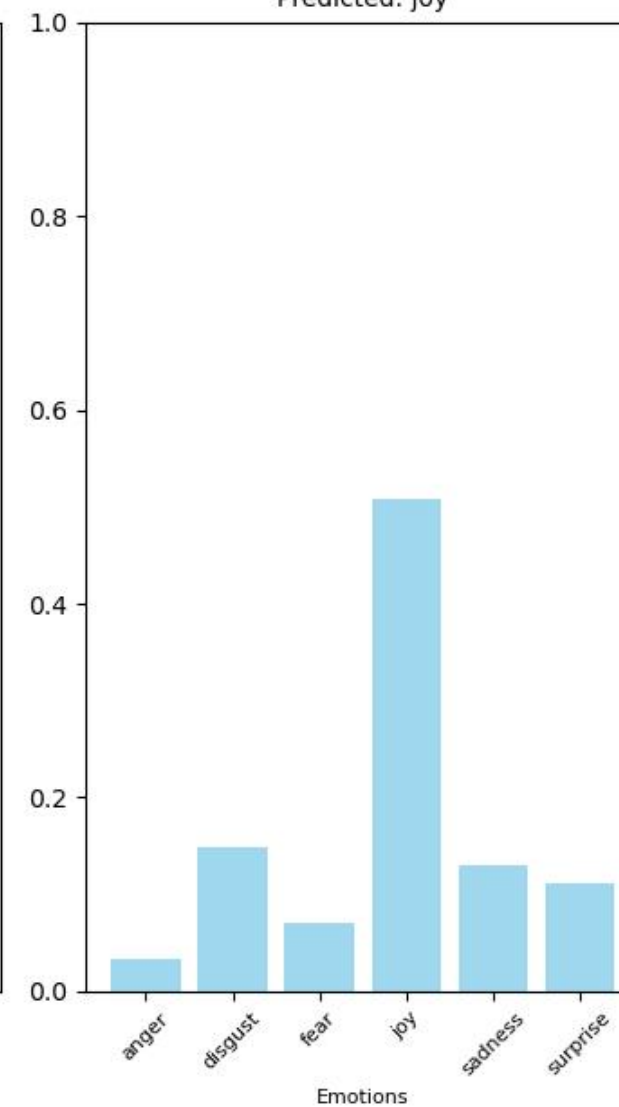


Image 4



Predicted: fear

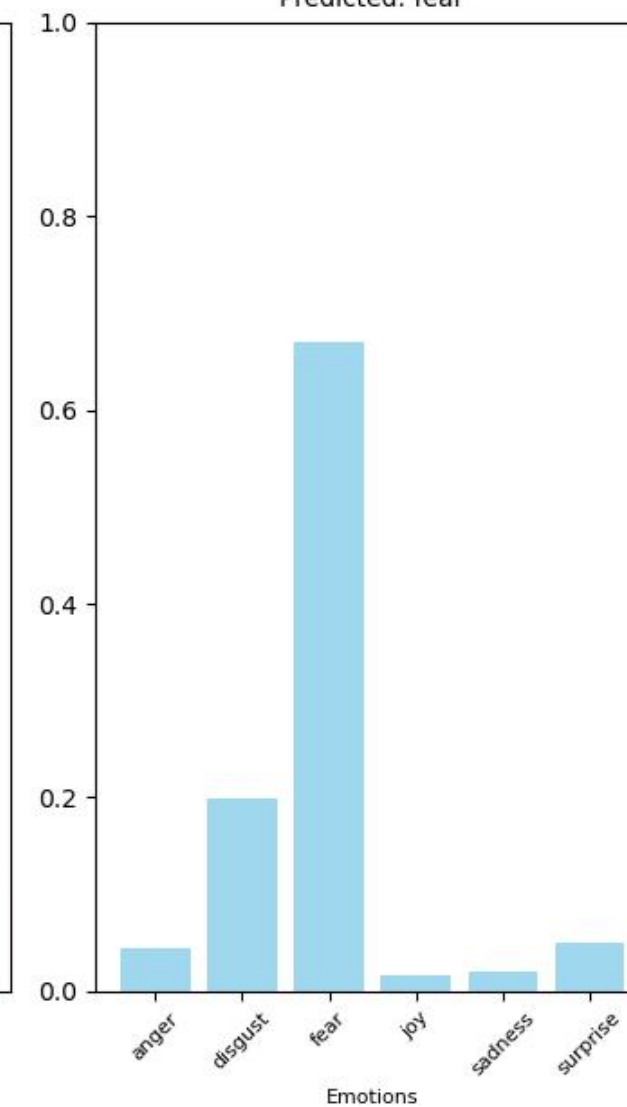
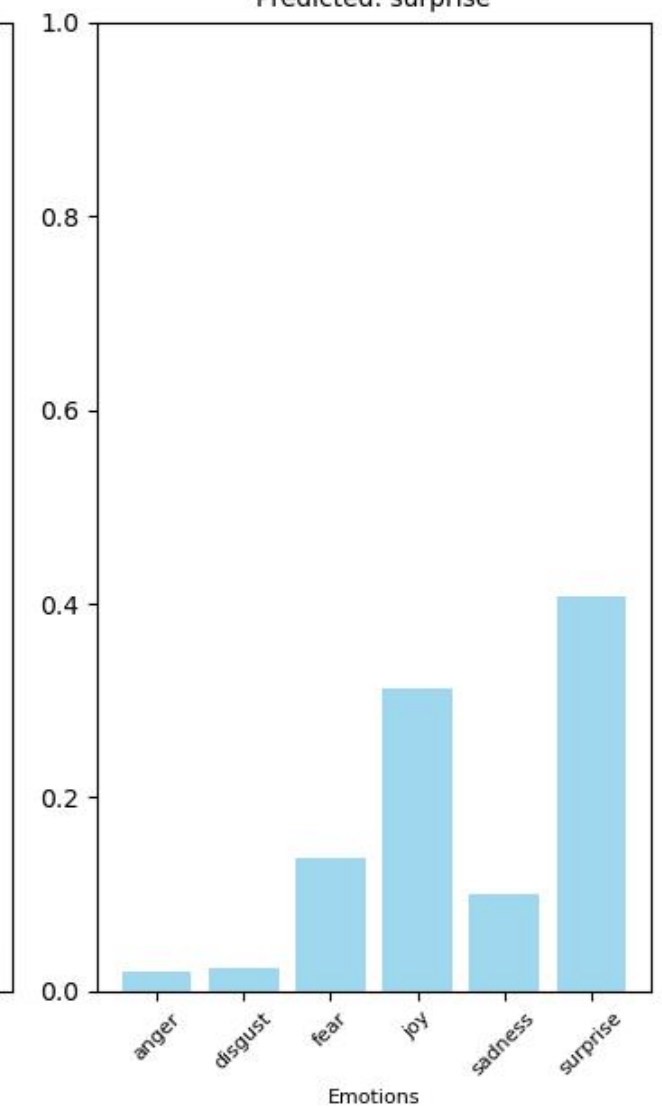


Image 5

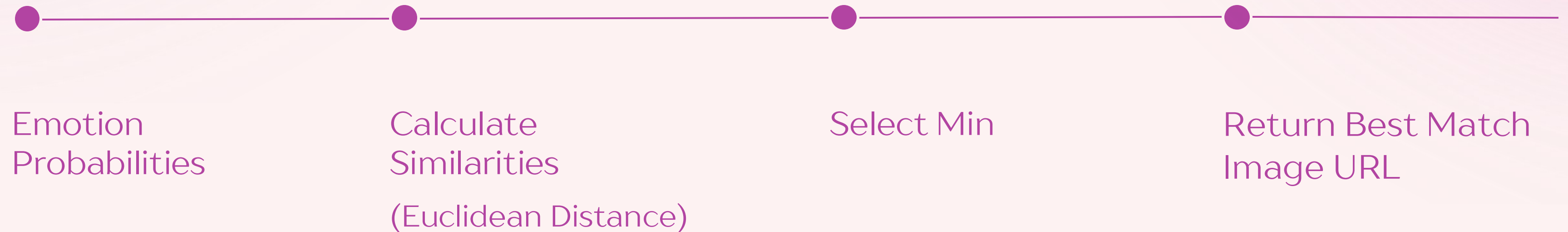


Predicted: surprise



# Emotion Similarity Matching

WikiArt Emotions dataset (Mohammad, 2018) pre-processing:  
20 emotions → filter to 6 → normalize distributions





# Style Transfer Module (S2WAT)



Gaudi Tower by A. M. Edulescu



Escher Sphere



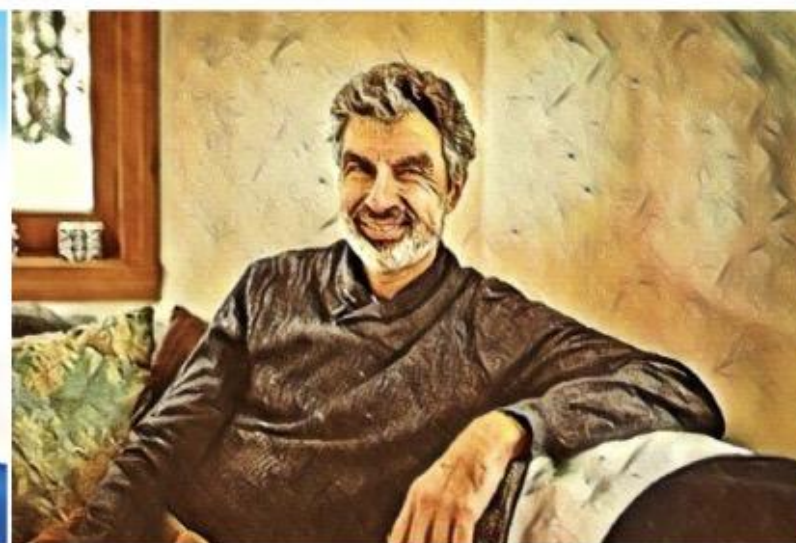
Starry Night



Mondrian



Unknown Style



Picasso Self Portrait



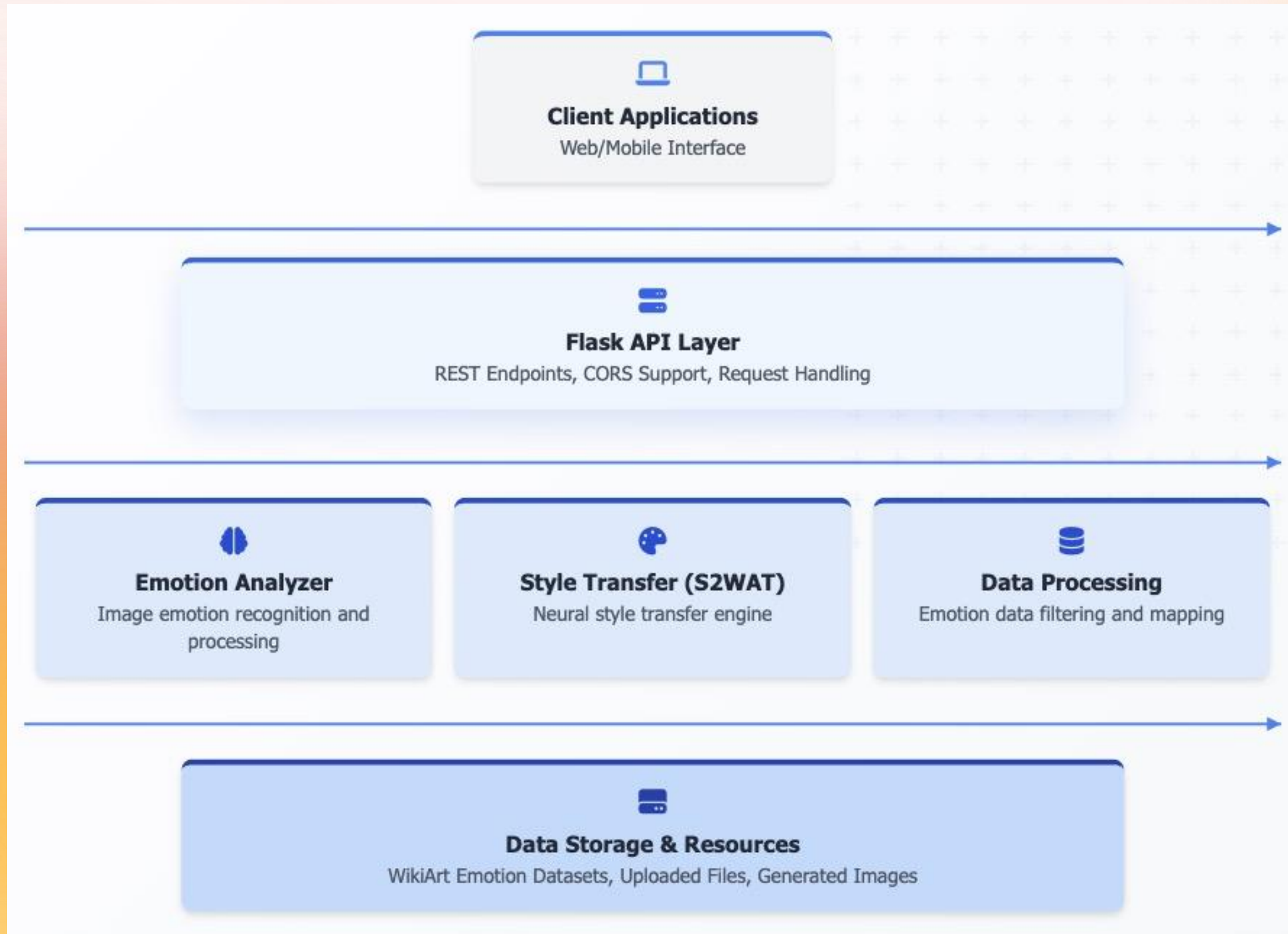
Blue Swirls



Candy



# Application Architecture



# API Endpoints and Workflow

## Upload Image

POST

/api/upload

Handles image upload with size validation, format checking, and secure storage.

## Analyze Emotion

POST

/api/analyze-emotion

Processes image to detect emotions, returns emotion probability distribution.

## Apply Style Transfer

POST

/api/style-transfer

Applies selected artistic to an upload image using S2WAT model.

## Get Emotion Artworks

GET

/api/emotion-artworks/{emotion}

Retrieves artwork recommendations based on specified emotion.



### Integration Architecture

All components work seamlessly together through a modular design pattern. The Flask backend orchestrates component interactions, handling API requests, input validation, and coordinating cross-component workflows for a complete emotion-to-art pipeline.



# Demo



## System Strengths



### Emotional Intelligence

Creates meaningful connections between images based on emotional content rather than just visual features



### Aesthetic Quality

Produces aesthetically pleasing results with emotional consistency using state-of-the-art S2WAT model



### Rich Artwork Database

Utilizes WikiArt Emotions dataset with ne-grained emotional annotations for diverse style matching



### Intuitive User Experience

Provides clear visualization of emotional analysis and interactive comparison of original and stylized images



## System Limitations



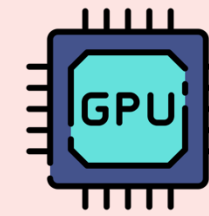
### Limited Emotion Spectrum

Restricted to six basic emotions, missing complex or mixed emotional states that are common in real-world images



### Variable Transfer Quality

Style transfer quality varies based on content-style image compatibility, despite emotional congruence



### Computational Demands

S2WAT model requires computational resources, limiting real-time processing on consumer hardware



### Cultural Bias

Emotional interpretation may be culturally influenced, affecting the universality of the emotion matching

# Reference

- Mohammad, S. M., & Kiritchenko, S. (2018). WikiArt Emotions: An annotated dataset of emotions evoked by art. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018). Miyazaki, Japan.
- Zhang, C., Xu, X., Wang, L., Dai, Z., & Yang, J. (2023). S2WAT: Image Style Transfer via Hierarchical Vision Transformer using Strips Window Attention [arXiv preprint arXiv:2210.12381]. <https://arxiv.org/abs/2210.12381>
- Chen Lab, Cornell University. (n.d.). Emotion6 [Dataset]. Retrieved April 22, 2025, from <http://chenlab.ece.cornell.edu/people/kuanchuan/publications/Emotion6.zip>