

Abstract:

Emotion-based style transfer using deep CNNs introduces an innovative approach that integrates emotions into style transfer, enabling the creation of emotionally enriched images.

Group Members & Contribution:

Dishant will be responsible for building, training, and fine-tuning the emotion recognition model.

Rahul will work on developing the style transfer network, and Dishant will support him in improving the network's performance.

We plan to share the workload for writing the project report and collaborate together during the integration phase, focusing on proper integration of both emotion recognition and style transfer models.

Motivation

Emotion-based style transfer has many applications like art creation, content personalization, and digital storytelling. It allows content creators to amplify the emotional impact of their visuals, offering new possibilities for emotionally engaging multimedia content.

Literature Review

We are exploring research on emotion recognition using deep learning techniques. Key papers and models in this area include "EmoReact" by Zhang et al. and the "FER+ Emotion Recognition" dataset. We are reviewing the literature on neural style transfer, including seminal works like "A Neural Algorithm of Artistic Style" by Gatys et al., which introduced the concept of style transfer using CNNs. We are also investigating the latest advancements in neural network architectures and pre-trained models like VGG, ResNet, and more.

Data

We plan to use established emotion datasets, namely, AffectNet and Fer2013, to train our emotion detection and style transfer models. To further improve the model generalization and performance, we may explore techniques like data augmentation and class weighting to offset imbalance in the datasets and we plan to use Google Colab GPU resources for model training.

Approach

Stage 1: Emotion Detection

We will train a CNN-based model for emotion detection from images, which will classify input images into emotion labels (e.g., happy, sad, anger), serving as a basis for the style to be used in the subsequent stage.

Stage 2: Style Transfer

Here, we will design a set of style transfer models. The process in this stage involves:

1. Model Training - For each emotion class, we will curate an emotion-specific datasets of images, along with a corresponding artistic style (e.g., melancholic for sad, vibrant for joyful).
 2. Adaptive Style Transfer - Upon detecting the emotion class from Stage1, we will dynamically apply the relevant style model associated with that class to the image, producing an output image aligned with the detected emotional state.
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Evaluation Metrics

- Style Transfer Quality: Metrics like Mean Squared Error (MSE), Structural Similarity Index (SSIM), or Peak Signal-to-Noise Ratio (PSNR) can be used to measure the quality of style transfer in terms of image fidelity and similarity to the reference style.
- Emotion Recognition Accuracy: Accuracy, F1-score, Precision & Recall will be used to assess its performance.

We will plot training curves that depict the change of style loss and content loss over iterations and also across various trained models.

References:

[1] Leon A. Gatys, Alexander S. Ecker, Matthias Bethg, A Neural Algorithm of Artistic Style

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[2] Behnaz Nojavanasghari, EmoReact: A Multimodal Approach and Dataset for Recognizing Emotional Responses in Children

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