

Art Suggester AI: The Art Recommendation Tool

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Abstract—Art Suggester is an AI-based art recommendation tool designed to inspire artists and enthusiasts by providing personalized art suggestions based on their available materials. The system uses a Convolutional Neural Network (CNN) to classify art mediums (e.g., paint, pencil crayons, markers) and a color detection algorithm to identify dominant colors in user-uploaded images. These inputs are used to recommend artworks from a curated database, making art discovery more accessible and engaging. Our CNN model achieved an accuracy of 95.12%, demonstrating its effectiveness in medium classification. The project highlights the potential of AI to bridge the gap between art creation and appreciation, offering a creative tool for artists and a learning resource for beginners. Code and resources are available at <https://github.com/McMasterAI2024-2025/ArtSuggesterAI>.

I. INTRODUCTION

Art Suggester addresses the challenge of artists having materials but lacking inspiration. By leveraging AI, the tool provides personalized art recommendations based on the materials and colors available to the user. This solution is significant because it enhances creativity, simplifies art discovery, and makes art more accessible to a broader audience [1]. Previous research has explored AI-driven art classification [2] and generative models [3], but few systems integrate medium identification and color analysis for tailored recommendations. Our approach combines CNN-based medium classification with color detection to offer a unique solution.

A. Motivation

Recent advancements in AI, particularly in CNNs and generative models, have made AI-driven art tools increasingly relevant [4]. CNNs having the ability to be trained on smaller datasets have improved image classification accuracy, enabling precise medium detection [5]. The global AI art market, valued at \$3.2 billion in 2024, is projected to grow to \$40.4 billion by 2033 [6], highlighting the growing interest in AI applications for creativity. However, existing tools often focus on style classification or generative art, leaving a gap for systems that integrate medium identification and color analysis. Art Suggester fills this gap by providing a tool that inspires artists and simplifies art discovery.

B. Related Works

Previous research has explored AI-driven art classification and recommendation systems. For example, CNNs have been

used for style and medium classification, while collaborative filtering has been applied for personalized recommendations. Generative models like DALL-E and Stable Diffusion have also gained popularity for creating art from text prompts [1]. However, these approaches often lack integration of medium and color analysis, which Art Suggester addresses.

C. Problem Definition

The Art Suggester faces challenges such as ensuring data quality and diversity for accurate medium detection, as maintaining model performance across varying image conditions (e.g., lighting, backgrounds) is difficult. We also need to have a variety of possible art recommendations with different styles and colours. Designing a user-friendly interface for the Art Suggester involves creating a secure user account system that caters to both artists and non-artists, adding complexity to the development process. The interface must feature intuitive navigation, ensuring users can easily upload images, view recommendations, and favourite art pieces. Balancing these challenges while delivering an accessible tool is key to the project's success.

II. METHODOLOGY

A. Data

We used a dataset comprising images from Google Images and custom photos of art materials (e.g., paint, pencil crayons, markers) taken under various lighting conditions. For recommendations, we utilized Kaggle datasets such as "Surreal Symphonies" [7] and "Portrait Paintings." [8] The data was preprocessed to 256x256 resolution and augmented to improve model robustness.

B. Model & Approach

We implemented a CNN using TensorFlow for medium classification. The model includes convolutional layers, dropout layers, and a softmax activation for classification. It was trained for 16 epochs with a validation split of 0.1 and a batch size of 16. We used the Adam optimizer with a learning rate of 0.001 and sparse categorical crossentropy as the loss function. For our color detection algorithm, we used the Python Imaging Library to detect color clusters and compare them to a predetermined list of colors, which were

also used to categorize our art pieces. Our database for users login information and favourite images were stored using MongoDB.

C. Evaluation

We evaluated the Art Suggester model using accuracy as the primary metric, measuring the percentage of correctly classified images, and employed confusion matrices to analyze performance on both a 10% test set and completely new images. This approach helped us assess the model’s generalization ability and identify areas where it struggled, such as distinguishing between specific classes like paint, pencil crayons, and markers. Validation was conducted using a 10% test set and additional unseen images to ensure accuracy. Challenges included ensuring dataset diversity to account for varying lighting conditions and backgrounds. As well as, addressing overfitting (memorizing training data rather than generalizing the patterns) through dropout layers and early stopping; and handling real world variability, such as low-quality images from user devices with poor lighting or resolution. We also did create models for a variety of epoch counts to compare them.

TABLE I
COMPARISON OF ACCURACY ACROSS DIFFERENT EPOCH COUNTS

Epochs	Training Accuracy	Unseen Data Accuracy	Loss
5	99.23%	11/14	0.0209
10	100%	11/14	0.00073
15	95.12%	12/14	0.0012
20	98.7%	9/14	0.004
25	99.7%	11/14	0.006

Our early stopping was based on if the loss would not change over around 10 epochs. We did this to reduce chances of overfitting. The early stopping would often stop at 15 epochs, along with the fact it was best at classifying completely unseen data with bad framing or resolution we decided to use 15 epochs for our final product. For our color detection, we achieved an accuracy of up to 85% for each uploaded photo. To improve the user experience and avoid potential mistakes from the algorithm, we added an option for users to manually adjust their color preferences before art pieces are suggested.

III. RESULTS

The CNN model achieved an accuracy of 95.12%, demonstrating its effectiveness in classifying art mediums. The color detection achieved an accuracy of up to 85% in detecting the medium’s colors. The confusion matrix (a graph to show model medium predictions compared to the actual medium) showed 174 correct classifications out of 189 test cases. The system successfully integrated medium classification and color detection to provide personalized art recommendations, outperforming traditional approaches in handling diverse art styles and simplicity of exploration.

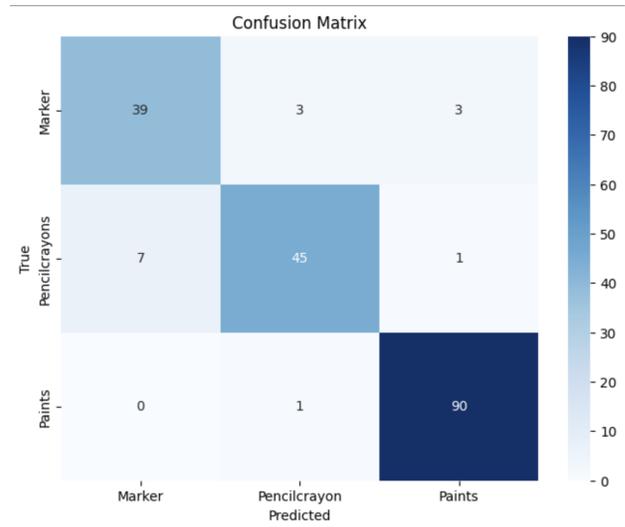


Fig. 1. Confusion Matrix of Test Data

IV. CONCLUSION

Art Suggester demonstrates the potential of AI to enhance art discovery by combining medium classification and color detection. The project achieved high accuracy and provided a user-friendly interface for personalized recommendations. Future work includes expanding the dataset, adding user feedback mechanisms, and optimizing the system for mobile devices. The tool has applications in art education, galleries, and interior design, making art more accessible and engaging for everyone. A detailed process flow diagram is below:

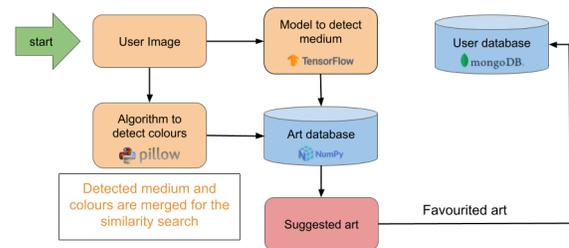


Fig. 2. Art Suggester AI Flow Diagram

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