SVM-powered Art Movement Identification

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***Abstract*— The vast and varied world of art, with its countless styles and approaches, presents a challenge for categorizing artworks. This is where technology comes in. The Support Vector Machine (SVM), known for its ability to find patterns in complex data like images, can be used to classify different art styles. Building on this, the project utilizes SVM on a dataset encompassing art styles like Japanese Art, Expressionism, and Primitivism.**

To improve accuracy and generalizability, we employed data augmentation techniques to enrich the dataset and grid search to optimize the SVM model's performance. This allows users to upload an image, and the trained model will predict its most likely art movement. Additionally, the project suggests images similar to the classified image. Through experimentation and evaluation, the project not only attains remarkable accuracy in classifying art movements but also enhances our understanding of the capabilities of Support Vector Machines (SVM) in identifying subtle features within artworks. This project brings together art and technology, helping to deepen our appreciation for how traditional art and modern machine learning can blend. The suggestions it offers are designed to inspire people to discover a wide variety of art styles, increasing their knowledge and enjoyment of art's vast and varied beauty.

I. INTRODUCTION

Art is the expression of human creativity and imagination through forms like painting and sculpture, created to evoke beauty or emotion. An art movement is a particular style or philosophy followed by artists in a specific period of time. Classifying art into movements helps us understand how artistic expression evolves within cultural, social, and political contexts. Understanding different art movements helps us appreciate the unique styles, methods, and beliefs that set each one apart. This knowledge makes it simpler to value the creativity and impact of artists throughout history. Categorizing art movements also aids in studying and teaching art history by providing an organized way to explore the wide range of visual culture. By recognizing these movements, we can see how historical events have shaped artistic trends and understand the connections between artists from different eras, enhancing our recognition of the vast creativity of humanity.

Since art comes in a wide variety of types and styles, each with its unique features and history, to better understand these characteristics, the images are classified using Support Vector Machines (SVM) in the project. SVM is a type of supervised machine learning algorithm that can classify artworks into various art movements. This algorithm is primarily used for classification, although it can also be used for regression problems. The goal of the SVM algorithm is to find the best hyperplane in a multi-dimensional space that can effectively separate the data points into different classes based on their features. The hyperplane aims to maximize the margin between the closest points of different classes. E.Cetinic et al.,[1,2] have developed image features inspired by Wölfflin's concepts, allowing regression models to identify meaningful stylistic properties in paintings. This demonstrates the usefulness of the features for users seeking artworks based on historically significant attributes. They utilized Convolutional Neural Networks (CNN) to classify art images, refining the models through fine-tuning and transfer learning to enhance accuracy in identifying artists, genres, styles, and nationality. In a study by S. Liu et al., they sought to enhance the classification of art movements by incorporating new features such as MCD and ColorRatio. Their research demonstrated impressive results on a collection of 927 paintings spanning six different artistic movements[3].

II. LITERATURE SURVEY

Support Vector Machine (SVM) has proven to be a reliable tool for categorizing images, particularly when confronted with data that is rich in dimensions. In a study performed by Chaganti et al., SVM was implemented in a small-scale image classification project, resulting in an impressive accuracy rate of 93% [1]. This initial investigation lays the groundwork for comprehending SVM's effectiveness in handling image-based information. Furthermore, a comparison conducted by Chandra, Mayank Arya and S.K. between SVM and alternative classification techniques highlights SVM's superiority in managing intricate data configurations [2]. Moreover, a comprehensive review by Kaur and Kaur sheds light on the characteristics of SVM and its relevance in image classification, underscoring the significance of SVM in this particular field [3]. In their comparative study, Anthony, Gidudu, Hali Gregg, and Marwala Tshilidzi analyze the differences between one-to-one (1vs1) and one-to-all (1vsM) methods in SVM-based image classification. They point out the trade-offs between computational complexity and classification efficiency, ultimately showcasing the benefits of the 1vsM approach[4]. In addition, J. Wu's development of the High-Order Intersection (HIK) SVM and the Intersection Coordinate Descent (ICD) algorithm is a major improvement in SVM-based image classification, providing valuable strategies for efficiently managing large datasets [5]. CNN revolutionized image classification by automating feature extraction and enhancing accuracy. Dhruv and Naskar's review offers a thorough analysis of CNN-based algorithms, highlighting the importance of deep learning in this field [6]. In a study by Abdullah and M.S. Hasan, they demonstrate the effectiveness of using pre-trained CNN models to improve classification tasks [7]. In a study led by Pasolli and his team, they explored the use of support vector machines (SVM) for image classification that incorporates spatial information through an active learning approach. Their findings demonstrate the benefits of selectively labeling samples to improve classification accuracy, providing a fresh insight into overcoming obstacles in supervised learning [8]. Abdullah and M.S. Hasan's research explores how using pre-trained CNN models can improve image classification by leveraging existing neural network structures. Their study highlights the potential efficiency gains and offers a solution to challenges in traditional supervised learning methods [9]. Zhang Chen and his team have shown that using Support Vector Machines for road vehicle classification highlights the algorithm's strength and precision in recognizing patterns within intelligent systems. Their work provides valuable insights into the practical applications of SVMs[10]. In their research on image classification using SVM, Xiaowu Sun and his team have shown that the algorithm is highly effective for both classification and regression tasks [11]. S. Koda and their team have developed a spatial and structured SVM for multilabel image classification, focusing on improving accuracy by incorporating spatial information and addressing the challenges of multiple-label scenarios [12]. A fascinating study discovered the potential for specialized SVM applications in agriculture and plant science by classifying coconut trees using the MIN-SVM model, extracting deep features, and utilizing the Inception Net for classification [13]. Another study concentrated on improving feature selection and classification for analyzing gene expression patterns using SVM-RFE and a rapid correlation-based filtering technique. The findings show progress in computational speed and precision in the field of bioinformatics [14]. The study[15] explores how variational mode decomposition affects the classification of EMG signals, highlighting the benefits of using SVM in processing medical and physiological signals. The research demonstrates how the algorithm can be effectively applied in different fields. Recent research on brain tumor detection has shown that a combination of CNN and SVM models can greatly enhance deep learning's capabilities in medical imaging and diagnostics. This study emphasizes the superior accuracy and loss metrics achieved by this hybrid model [16]. Efforts to enhance cancer classification algorithms have focused on reducing noise in data and streamlining classification processes. By incorporating various feature selection techniques, researchers are continuously striving to optimize SVM applications in health informatics [17]. In psychology and forensics, using SVM for handwriting classification to predict behavior is an interesting application of the algorithm. It demonstrates SVM's versatility and broad range of uses[18]. The development of a graphical interface for categorizing art movements with SVM, along with data enhancement methods, shows the creative application of SVM in the cultural and artistic field. This enhances the user's experience in discovering and enjoying art[19].

The project includes a user-friendly graphical interface that adds a hands-on element to the classification system. Users can easily upload images and get classifications based on predicted art movements. They can also obtain personalized art history suggestions.

III. METHODOLOGY

The project methodology follows a structured approach that includes the following steps. We use Support Vector Machines (SVMs) for Image Classification based on mathematical principles. The first task is to load the provided datasets to build a predictive model for images. These datasets consist of various image categories. Once the datasets are loaded, they are divided and used for training to determine accuracy.

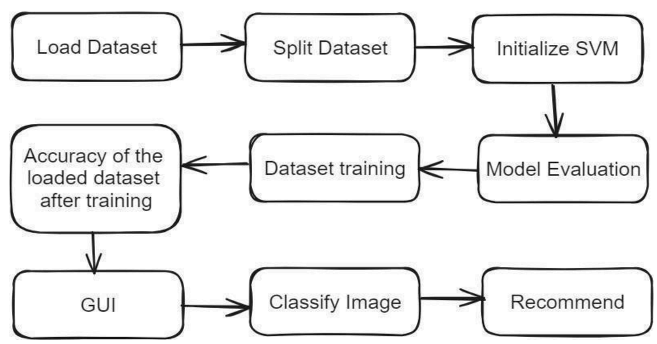

Fig. 3.1. End-to-end Pipeline

Starting by uploading our dataset, every image is resized to 150x150 pixels to keep it consistent and then flatten it into a one-dimensional array. This makes the images simpler while still maintaining their key characteristics, making them perfect for machine learning studies. The flattened images, along with their respective categories, are saved in arrays, getting the dataset ready for the following stages.

Once the dataset is prepared, it is split into training and testing sets using a 20% split ratio. This separation allows to train our model on a portion of the data (training set) and then test its performance on unseen data (testing set), ensuring that our model can generalize well to new, unseen images. The splitting process is stratified by the target variable (art styles), ensuring that each art style is proportionately represented in both the training and testing sets.

The SVM model was initialized and then trained on the training set. SVM is preferred due to its ability to effectively handle high-dimensional data and model intricate boundaries between various classes. To determine the optimal parameters for the SVM model, we utilize GridSearchCV. This method systematically explores different combinations of parameter settings while cross-validating to identify the set of parameters that yields the best performance. Following the training phase, we choose the model with the most favorable parameters.

The model's effectiveness is assessed by using a confusion matrix, which gives valuable information about the model's accuracy and where it may be getting mixed up in identifying different artistic styles. This process allows us to better grasp how effective the model is at accurately sorting images into their corresponding art categories.

Tkinter was used to create a user-friendly graphical interface for interacting with the model. Users can submit images to be categorized by art style. The model then predicts the style of the image and shows the result, including the accuracy of the prediction. Furthermore, the interface suggests similar images from the dataset in the same style as the submitted image. This showcases the practical use of the model and encourages users to explore different art styles through the recommended images.

IV. EXPERIMENTS AND EVALUATIONS

Dataset Selection: The model for classifying images was trained and tested using a high-quality dataset. This dataset contained a wide range of art styles, carefully selected to represent various visual characteristics. It featured images showcasing Japanese Art, Expressionism, and Primitivism, providing diversity in artistic styles. The dataset was sourced from Kaggle, originally curated by Sivar Azadi, and made available to the public domain without any copyright restrictions. Therefore, it was an ideal dataset to use for this project.

Data Preprocessing: During the initial phase of data preparation, it was crucial to resize and flatten images, with a consistent choice of 150x150 pixels for all images. This particular size was carefully selected to strike a balance between computational efficiency and the ability to maintain important features required for the Support Vector Machine (SVM) model to accurately distinguish between different art styles. By using a resolution of 150x150, the processing task becomes more manageable, reducing the computational burden while still capturing the necessary detail in terms of color, texture, and shape which is vital for recognizing subtle distinctions in art movements. This aspect finds a balance between reducing the chance of overfitting by not bombarding the model with excessive information and ensuring there is enough data to prevent underfitting, allowing for a consistent input format throughout the dataset. The decision is based on both actual test results and practical knowledge of image categorization, improving the model's efficiency by striking a harmony between image clarity and processing speed.

Model Selection: For this project, the Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel as the main classification algorithm was chosen. SVMs are popular for their ability to work well with high-dimensional data, making them ideal for tasks like image classification. We used the GridSearchCV technique to fine-tune the model's hyperparameters, improving its performance.

Hyperparameter Tuning with GridSearchCV: The next experimentation involved hyperparameter tuning using GridSearchCV. This method explores a range of parameter options (such as C, gamma, and kernel for the SVM) to find the combination that results in the best model performance. By training multiple models with different parameter combinations and evaluating their performance, the project identified the most effective settings for the SVM model. This step is vital for optimizing the model's ability to classify images accurately, as the choice of parameters significantly impacts the model's learning process and overall accuracy.

Model Evaluation with Confusion Matrix: Upon completion of training, the model underwent evaluation through the use of a confusion matrix. This method allowed for a thorough analysis of the model's classification performance across various art styles. By comparing the predicted art styles with the actual labels within the test set, the confusion matrix not only displayed the overall accuracy but also highlighted specific instances of misclassification. This evaluation process is crucial in identifying both the strengths and weaknesses of the model, thereby facilitating adjustments to enhance its accuracy. Fig 4.1 shows the obtained confusion matrix.

Training and Testing Split: The dataset was strategically divided into training and testing sets, maintaining an 80-20 ratio. This division allowed the model to learn intricate patterns and features from the training data, enabling it to generalize well to unseen images. The testing set served as a benchmark to evaluate the model's performance on instances it had not encountered during training.

***Performance Metrics*:** To quantify the model's performance, the following key metrics were utilized:

Accuracy: Accuracy served as the primary metric, providing a straightforward measure of the model's overall correctness in classifying instances within the test set. It represented the proportion of correctly classified instances out of the total.

Fig. 4.1 Confusion Matrix

V. RESULTS AND DISCUSSIONS

The project details the outcomes and insights gained from implementing the image classification model in practical scenarios. This segment analyzes the model's performance, precision, and overall efficacy in predicting art styles. It discusses the assessment criteria, including accuracy ratings and confusion matrices, to highlight the strengths of the model and identify areas for enhancement.

A. ROOT WINDOW

Fig. 5.1. Root Window

The main interface for the Art Style Classifier application is the root window of the GUI. It was built with the Tkinter library to ensure ease of use. The window is labeled "Art Style Classifier" and contains important elements like buttons and labels. By clicking the "Classify Image" button, users can start the image classification process and choose an image for style prediction. The "Recommend Images" button provides suggestions for related images based on the predicted art style as shown in Fig 5.1.

B. CLASSIFY IMAGE

The "Classify Image" button found in the GUI (shown in Figure 5.1) is what the user clicks to start the image classification process. Once clicked, it prompts the user to choose an image file from their device using a file dialogue. The chosen image is then loaded into the system, resized to a standard size of 150x150 pixels, and flattened to extract its pixel information. This preprocessed image data is then input into the trained Support Vector Machine (SVM) model, which predicts the art style category of the image. The label on the screen updates in real time to show the predicted art style based on the SVM's classification. The functionality of the "Classify Image" button thus allows users to interactively classify individual images, gaining insights into the predicted art style with each selection as shown in Fig. 5.1.

C. RECOMMEND IMAGES

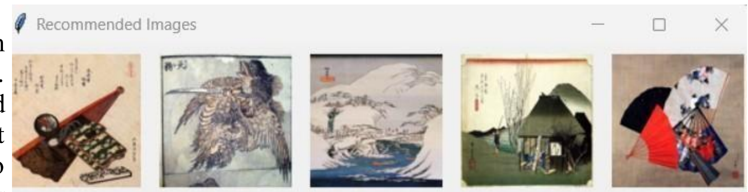

Fig. 5.2. Recommend Images

The "Recommend Images" button on the interface helps users by suggesting more images that match the predicted art style of a classified image as shown in Fig 5.2. After using the "Classify Image" button to predict the art style, the "Recommend Images" button kicks in. It takes the predicted art style from the result label and then finds the folder in the dataset with images of that same art style. The button shows a list of files in the predicted art style folder and chooses up to five images at random to display. These images appear in a separate window, providing users with a visual recommendation based on the predicted art style. This feature enhances user interaction by enabling them to view additional examples of the predicted art style and appreciate the variety within that category. The window closes automatically after five seconds to ensure a smooth user experience.

VI. CONCLUSION

In conclusion, the Art Style Classifier and Recommender System offers a user-friendly way to explore different art styles through image classification. The project effectively analyzes image data from various art categories using a Support Vector Machine (SVM) model for precise classification. The Tkinter graphical user interface (GUI) improves user engagement by enabling users to upload images and get predictions for their art styles. Model persistence with Pickle guarantees efficiency by saving and loading the trained SVM model. The User Interface (UI) automatically updates information by showing the expected art style for categorized images, giving users the choice to discover more recommendations within the same art style. The random assortment of suggested images brings diversity to the user's interaction. Furthermore, there are potential enhancements in store for the project, such as implementing advanced deep-learning techniques, instant image classification, and mechanisms for users to provide feedback. Essentially, the Art Style Classifier and Recommender System serves as an educational and exploratory tool in the realms of image categorization, machine learning, and art appreciation. With its simple layout and useful functions, it is both user-friendly and attractive to those with a passion for art.

VII. FUTURE SCOPE

To improve the project, further exploration of advanced image classification methods such as Convolutional Neural

Networks (CNNs) for a deeper understanding of image patterns would be required. Using transfer learning with pre-trained models like VGG, ResNet, or Inception can enhance accuracy by adapting them to your specific requirements. Implementing feature reduction techniques like Principal Component Analysis (PCA) can help simplify the data while preserving important details. Take advantage of parallel processing and, if feasible, distributed training on multiple devices to increase efficiency, particularly when dealing with large datasets or complex models. Broadening the dataset to encompass a wider range of art styles, along with implementing user authentication for personalized recommendations, could also be beneficial.

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