SVM-powered Art Movement Identification

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***Abstract*— Artistic expression spans diverse movements and styles, each encapsulating unique characteristics and cultural influences. The project uses Support Vector Machines (SVM), to classify artworks into distinct art movements. The dataset comprises images from various movements such as Japanese Art, Expressionism, and Primitivism. The key innovation lies in utilizing the power of SVM, a robust and versatile classification algorithm, to discern intricate patterns in high-dimensional image data.**

Data augmentation techniques, enrich the dataset, enabling the model to generalize better across diverse artistic styles. The project employs a rigorous grid search for hyperparameter tuning, optimizing the SVM model's performance. The user-friendly graphical interface users to upload an image, where the SVM model, trained on an array of art movements, predicts the most likely art movement to which the artwork belongs. Recommendations for further exploration of art movements are provided based on the predicted movement, offering users a curated journey through art history. Through experimentation and evaluation, this project not only achieves high classification accuracy but also sheds light on the interpretability of SVM in distinguishing nuanced features within artworks. This work contributes to the intersection of art and technology, fostering a deeper appreciation for combining traditional aesthetics and cutting-edge machine learning. The provided recommendations aim to encourage users to explore a diverse range of art movements, enhancing their understanding and appreciation of the rich tapestry of artistic expression.

I. Introduction

In this project, we embark on a journey into the world of art-style classification using machine learning, specifically Support Vector Machines (SVM). The objective is to develop a robust model capable of classifying artworks into distinct art movements, each possessing unique characteristics and cultural influences. Our dataset is a compilation of images representing various art movements, including but not limited to Japanese Art, Expressionism, and Primitivism.

To ensure the model's ability to discern intricate patterns in high-dimensional image data, we start by loading and augmenting the dataset. The images are resized to a consistent 150x150 pixels and then flattened for further processing. Data augmentation techniques are applied to enrich the dataset, promoting better generalization across diverse artistic styles.

The dataset is then split into training and testing sets, and additional preprocessing steps. The SVM model is trained using a grid search for hyperparameter tuning, optimizing its performance. The best parameters obtained from the grid search are utilized to train the final SVM model, which is then saved for deployment.

To assess the model's accuracy and performance, predictions are made on the test set. The SVM model is loaded, and the test set is processed using the same preprocessing steps applied to the training set. Predictions are made, and the model's accuracy is evaluated using metrics such as accuracy score and classification report.

The project provides a comprehensive pipeline involved in art style classification, from data loading and preprocessing to model training and evaluation. This project not only demonstrates the application of machine learning in the realm of art but also sets the stage for further exploration and understanding of the intricate features that define different art movements.

II. Literature Survey

The research paper titled "Image Classification Using SVM and CNN," authored by Chaganti, Sai Yeshwanth, et al., and presented at the 2020 International Conference on Computer Science, Technology, and Applications (ICCSEA), introduces the utilization of Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for image classification. The team opted for a small-scale image classification approach, employing minimal hardware resources. The initial phase involved the use of SVM with a limited dataset, resulting in an impressive 93% accuracy. The paper extensively reviews the applications of CNNs and deep learning in the field of image classification. To provide a comprehensive overview of CNNs in this context, the authors reference the work titled "Review of Image Classification Algorithms Based on Convolutional Neural Networks" by Dhruv and Naskar. Notably, this referenced paper discusses various CNN architectures, classic models, and their successful applications in image classification, achieving a notable 94%

accuracy across three distinct classes[1]. The publication authored by Chandra, Mayank Arya, and S.K. delves into fundamental aspects of Support Vector Machines (SVM), exploring its fundamental concepts, modifications, and role in image classification applications. The paper conducts a comparative analysis between SVM and alternative classification methods such as k-NN, decision trees, and neural networks. The authors conclude that SVM emerges as a potent tool for image segmentation, particularly in scenarios involving high-dimensional data processing. For an in-depth examination of SVM and its practical applications in image classification, the work of Kaur and Kaur, titled "Analysis of Image Classification Using SVM," presents a comprehensive overview encompassing SVM properties and its utilization in image classification[2]. The paper titled "Image classification using SVMs: one-to-one vs. one-to-all," authored by Anthony, Gidudu, Hali Gregg, and Marwala Tshilidzi, and published on arXiv in 2007, conducts a comparative analysis between one-to-one (1vs1) and one-to-all (1vsM) methods in Support Vector Machine (SVM)-based image classification. The authors meticulously outline the advantages and disadvantages associated with each approach while exploring the practical application of SVM in image classification scenarios. The paper places particular emphasis on the computational intricacies of the 1vs1 approach, especially in scenarios involving numerous classes. Additionally, it highlights the potential for improved generalization and reduced redundancy offered by the 1vsM approach. The study significantly contributes to the understanding of classification conditions and performance, offering valuable insights for researchers and practitioners in the field[3]. The 2012 paper titled "Efficient HIK SVM Learning for Image Classification," authored by J. Wu published in the IEEE Transactions on Image Processing, is dedicated to advancing machine learning techniques in the realm of image classification. The paper introduces the High-Order Intersection (HIK) SVM along with the Intersection Coordinate Descent (ICD) algorithm, with a primary focus on enhancing efficiency and scalability for large-scale image classification tasks. Conducting a thorough literature survey, the paper offers a comparative analysis of HIK SVM against alternative methods, providing valuable insights for the research community. The study underscores the effectiveness of HIK SVM in managing substantial datasets and addressing computational demands, establishing it as a powerful tool in the field of image classification[4]. The 2002 paper titled "Unsupervised approach for polarimetric SAR image classification using support vector machines," authored by S. Fukuda, R. Katagiri, and H. Hirosawa, and presented at the IEEE International Geoscience and Remote Sensing Symposium, delves into the utilization of support vector machines (SVMs) for the unsupervised classification of polarimetric synthetic aperture radar (SAR) images. The paper underscores the significance of polarimetric SAR image classification, highlighting SVMs' adeptness in managing high-dimensional data. Additionally, it emphasizes the efficacy of unsupervised approaches in handling large-scale remote sensing data. Drawing on insights from prior research, the paper contributes valuable perspectives on the role of SVMs in the effective classification of polarimetric SAR images, with implications that extend to geoscience and remote sensing applications[5]. The 2014 paper titled "SVM Active Learning Approach for Image Classification Using Spatial Information," authored by E. Pasolli and a team, and published in the IEEE Transactions on Geoscience and Remote Sensing, introduces an active learning strategy for image classification employing support vector machines (SVMs) and spatial information. The paper delves into the exploration of active learning coupled with SVMs in the context of image classification, emphasizing the incorporation of spatial information to augment accuracy. It scrutinizes the challenges encountered in conventional supervised learning for image classification, underscoring the potential of active learning methodologies to address these challenges by judiciously selecting informative samples for labeling. The paper draws on prior research, presenting a comprehensive overview of advancements in SVM active learning. This scrutiny provides valuable insights into the utilization of active learning and SVMs for image classification, particularly in domains like remote sensing and geoscience, with implications for enhancing both accuracy and efficiency[6]. The 2017 paper titled "Application of Pre-trained CNN for Image Classification" authored by Abdullah and M.S. Hasan, and presented at the 20th International Conference of Computer and Information Technology, investigates the utilization of pre-trained convolutional neural networks (CNNs) in image classification. The review of literature emphasizes the substantial role played by CNNs in image classification, particularly in the context of enhancing accuracy and efficiency through the use of pre-trained models. The paper explores the challenges inherent in traditional supervised learning for image classification, highlighting the way pre-trained CNNs effectively tackle these challenges by leveraging features acquired from extensive datasets. Drawing upon earlier research, the paper provides a comprehensive overview of advancements in CNN-based image classification. This analysis imparts valuable insights into the application of pre-trained CNNs for efficient image classification, thereby contributing to a broader comprehension of classification methods in the realm of computer vision[7]. The 2009 paper titled "Road Vehicle Classification using Support Vector Machines," authored by Z. Chen and team, and presented at the IEEE International Conference on Intelligent Computing and Intelligent Systems, introduces a pragmatic approach to road vehicle classification employing kernelized Support Vector Machines (SVM). The literature review accentuates the significance of SVMs in pattern recognition, particularly in the domain of road vehicle classification, emphasizing their robustness and accuracy. The paper delves into the challenges associated with traditional methods of vehicle classification and underscores the potential of SVMs to offer an efficient technique for pattern recognition. Drawing upon earlier research in SVM-based vehicle classification, the paper provides a comprehensive overview of advancements in the field. This analysis imparts valuable insights into the utilization of SVMs for road vehicle classification, contributing to the development of effective classification methods with implications for intelligent systems[8]. The 2015 paper titled "Image Classification via Support Vector Machine" by Xiaowu Sun and the team, presented at the 4th International Conference on Computer Science and Network Technology, delves into the utilization of support vector machines (SVMs) for image classification. The literature review underscores the significant role played by SVMs in image classification, highlighting their robustness and efficiency as both a classification and regression algorithm. The paper explores challenges and trends within SVM classification, offering a comprehensive overview of the field's advancements. This analysis provides valuable insights into the effective application of SVMs for image classification, thereby contributing to our understanding of classification methods in computer vision and related domains[9]. The 2018 paper titled "Spatial and Structured SVM for Multilabel Image Classification" authored by S. Koda and team, and published in the IEEE Transactions on Geoscience and Remote Sensing, introduces an innovative approach to multilabel image classification using spatial and structured support vector machines (SVMs). The literature review underscores the significant role that SVMs play in image classification, particularly in scenarios involving multiple labels, and addresses the challenges associated with such scenarios. It explores how structured SVMs can integrate spatial information and dependencies between labels to address these challenges. The paper makes references to prior works, providing a comprehensive overview of advancements in SVM-based image classification. This analysis contributes valuable insights into the effective use of structured SVMs for multilabel image classification, enhancing our understanding of classification methods in remote sensing and related fields[10]. The aim of the study in the paper[11] was to classify coconut trees based on height, inclination, and orientation using the proposed MIN-SVM classification model. The methodology involved pre-processing raw images, extracting deep features using LBP, HOG, and PCA feature extractors, and feeding them to the Inception Net. The MIN-SVM model achieved a testing accuracy of 95.35% and outperformed other CNN models. However, the study did not have access to a public dataset for coconut trees, leading to the need for a large dataset and the potential overlapping of samples among classes, which could affect accuracy and robustness[11]. The research in [12] aims to enhance feature selection and classification for gene expression profiling, with a focus on reducing computational time and increasing overall accuracy. The methodology involves utilizing the efficient SVM-RFE embedded method, along with a fast correlation-based filter to improve performance. The results indicate that the ISVM-RFE method outperforms existing methodologies, decreasing computation time while improving accuracy. However, a potential disadvantage lies in the increased computational time associated with large-scale linear support vector machines (LLSVM) when handling massive datasets, highlighting the need for further optimization in this area[12]. The motivation for the study[13] was to investigate the impact of variational mode decomposition (VMD) on the classification of electromyographic (EMG) signals from the soleus muscle during different walking conditions. The methodology involved collecting EMG signals during forward and reverse walking on even and uneven surfaces with inclinations of 0o and 10o, extracting features from VMD-based components, and evaluating the classification accuracy using Support Vector Machines (SVM). The results indicated that the VMD-based features yielded high accuracy in classification across various walking conditions, outperforming raw signals. However, a potential disadvantage of VMD-based processing is the increased computational complexity compared to using raw signals[13]. The study in [14] aimed to develop an effective method for brain tumor detection using deep learning technology. The methodology involved the creation of a 19-layer hybrid CNN-SVM model, utilizing pre-trained models such as InceptionV3 and ResNet50, and training a custom CNN model with 50 layers. The study experimented with a brain tumor dataset of 3645 MRI images and compared the predictions between the plain CNN model and the CNN-SVM model. The results showed that the CNN-SVM model achieved a validation accuracy greater than the CNN model and had lower values of loss and validation loss. However, the study did not explicitly mention any disadvantages of the proposed approach[14]. The study in [15] aims to improve the accuracy of cancer classification algorithms by reducing noisy data and minimizing classification time. The methodology involves using a combination of feature selection methods, including SU, Relief, and SVM, to select the most relevant features from the microarray dataset. Experimental analysis of the Leukaemia dataset demonstrates improved accuracy and reduced computational time, with the combination of algorithms outperforming individual methods. However, a potential disadvantage is the complexity of integrating multiple feature selection techniques, which may require additional computational resources and expertise[15]. The aim of the study is[16] to analyze different types of handwriting and classification using a Support Vector Machine (SVM), with a focus on revealing behavioral predictions through computer-aided analysis. The methodology involves capturing handwriting samples, extracting time-domain features, and classification using SVM, with a specific focus on trajectory, speed, and acceleration analysis without human intervention. The results indicate that the system has an accuracy varying from 92.33% to 62.5% while predicting the signal, and the average time taken for writing a sentence was 17 seconds. However, the study does not explicitly mention any disadvantages of the proposed system[16].

The project introduces a user-friendly graphical interface, offering a practical and interactive dimension to the classification system. Users can seamlessly upload images, receive classifications based on predicted art movements, and explore personalized art history recommendations. A distinct feature lies in the incorporation of data augmentation techniques, such as random rotations, aimed at enriching the dataset and improving model generalization across diverse artistic styles. The project also undertakes a comparative analysis of SVM modifications, discussing their efficacy for image segmentation and highlighting their interpretability in distinguishing nuanced features within artworks.

III. METHODOLOGY

The methodology of this project employs a systematic process involving the following mentioned processes. We apply the mathematical basis of the Support Vector Machines (SVMs) for the Image Classification. To build a model which can predict images the first step would be loading the given datasets in it. The dataset contains the different categories of images Once, the dataset is loaded it splits the model and starts training and finding the accuracy.

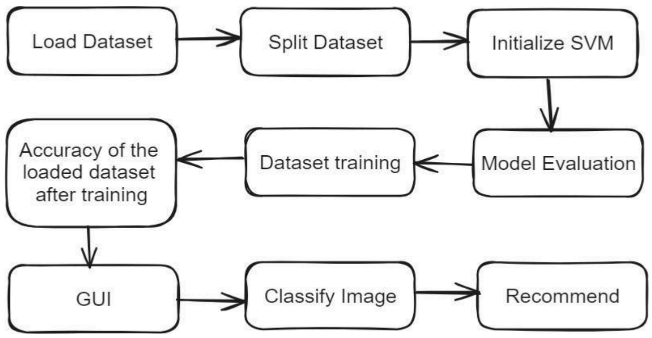

Fig. 3.1. End-to-end Pipeline

A. LOADING THE DATASETS

The code systematically collects images from specified folders, methodically organizing them into a well-structured data frame for model training and testing. It commences by specifying the categories of images to be identified. Subsequently, it systematically traverses through each category folder, loading individual images, ensuring uniformity by resizing them, and systematically flattening their pixel data to facilitate efficient processing. The meticulously organized flattened image data and their corresponding category labels are then methodically compiled into separate arrays, seamlessly integrated into a pandas frame. This data frame serves as a well-defined and easily accessible groundwork for subsequent stages of model training and evaluation.

B. SPLIT THE DATASET

To ensure impartial model training and assessment, the code strategically partitions the prepared image dataset into two distinct subsets: a training set and a testing set. This partitioning is meticulously carried out using the train_test_split function, maintaining a balanced 80/20 ratio. The training set, constituting 80% of the data, functions as the primary source for the model's learning process, allowing it to uncover underlying patterns and relationships within the images. The remaining 20% is deliberately allocated as the testing set, providing an unbiased evaluation of the model's accuracy and its capacity to generalize to new images. This intentional division mitigates the risk of overfitting and enhances the model's effectiveness in accurately classifying previously unseen images.

C. INITIALIZE SVM:

The code harnesses the capabilities of an SVM classifier through a meticulous two-step process: precision tuning and dedicated training. Employing GridSearchCV, it systematically fine-tunes essential parameters akin to adjusting a telescope lens, with the primary goal of optimizing accuracy. Subsequently, resembling the method of teaching a student through flashcards, it exposes the SVM to an extensive array of categorized images, enabling it to discern the nuanced features that differentiate, for instance, Expressionism from Primitivism. This thorough procedure effectively transforms the SVM into a robust image classifier, well-equipped to handle diverse, unseen images with accuracy and confidence.

D. MODEL EVALUATION:

Following the thorough training of the SVM, the code scrutinizes its performance akin to a proud teacher reviewing a student's assignments. It challenges the model with unseen test images, meticulously observing its predictions with keen attention. Metrics such as the accuracy score serve as precise measures of its success, laying bare the extent of its classification precision. Delving deeper, confusion matrices provide insights into specific areas where the model encounters challenges, offering valuable cues for subsequent learning and enhancement. This rigorous evaluation process guarantees that the SVM is well-prepared for real-world applications, demonstrating its proficiency in confidently recognizing images and establishing itself as a dependable image classifier.

E. DATASET TRAINING:

Following the thorough training of the SVM, the code scrutinizes its performance akin to a proud teacher reviewing a student's assignments. It challenges the model with unseen test images, meticulously observing its predictions with keen attention. Metrics such as the accuracy score serve as precise measures of its success, laying bare the extent of its classification precision. Delving deeper, confusion matrices provide insights into specific areas where the model encounters challenges, offering valuable cues for subsequent learning and enhancement. This rigorous evaluation process guarantees that the SVM is well-prepared for real-world applications, demonstrating its proficiency in confidently recognizing images and establishing itself as a dependable image classifier.

F. ACCURACY OF THE LOADED DATASET AFTER TRAINING:

Post-training, the model faces a stringent test on the unseen testing set, akin to a champion undergoing a challenging competition. Its prowess is meticulously assessed, much like a champion's score, utilizing metrics such as accuracy score to unveil the percentage of precise predictions. Delving deeper, confusion matrices meticulously analyze their performance, pinpointing potential vulnerabilities in specific categories. This rigorous evaluation guarantees that the model is not merely a facade but a genuine champion in image classification, equipped to confront real-world challenges with justified confidence in its accuracy.

G. GRAPHICAL USER INTERFACE:

The graphical user interface (GUI) in this project, created using the Tkinter library, facilitates user interaction with the image classification model. The GUI's main window, titled "Art Style Classifier," features buttons for image classification and recommendation. The "Classify Image" button allows users to select an image for style prediction, with results dynamically displayed. The "Recommend Images" button provides image suggestions based on the predicted style. The GUI incorporates informative labels, such as "Predicted art style," offering clear user feedback. Overall, the GUI enhances user accessibility and engagement with the image classification functionalities.

IV. EXPERIMENTS AND EVALUATIONS

Experimental Setup: For the evaluation of the image classification model, a well-defined set of experiments was conducted to gauge the model's accuracy and generalization performance. The following components were considered in the experimental setup:

Dataset Selection: The image classification model was trained and evaluated using a meticulously curated dataset. This dataset encompassed a rich variety of art styles, deliberately chosen to cover a broad spectrum of visual characteristics. Notably, the dataset included images representing Japanese Art, Expressionism, and Primitivism, ensuring diversity in artistic styles. The data set was taken from Kaggle which was published by Sivar Azadi as a public domain with no copyright. Hence, seemed to be the perfect dataset to work on.

Data Preprocessing: Before model training, a crucial step involved preprocessing the images. This included resizing all images to a standardized dimension of 150x150 pixels. Standardizing the dimensions facilitated effective model training by ensuring consistent input sizes across all images. This preprocessing step aimed to enhance the model's ability to learn relevant features from the images.

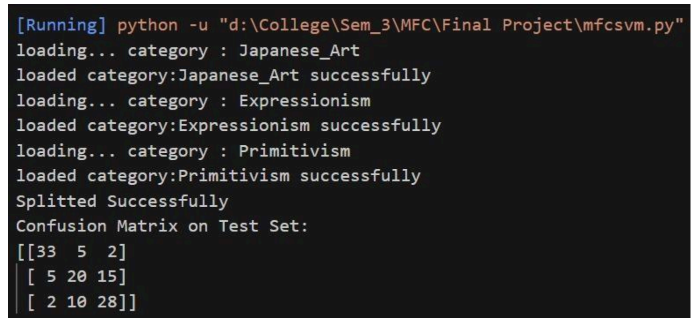

Fig. 4.1. Data Preprocessing

Model Selection: The primary classification algorithm chosen for this project was the Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. SVMs are known for their effectiveness in handling high-dimensional data, making them well-suited for image classification tasks. The model's hyperparameters were fine-tuned using the GridSearchCV technique, optimizing its configuration for better performance.

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.

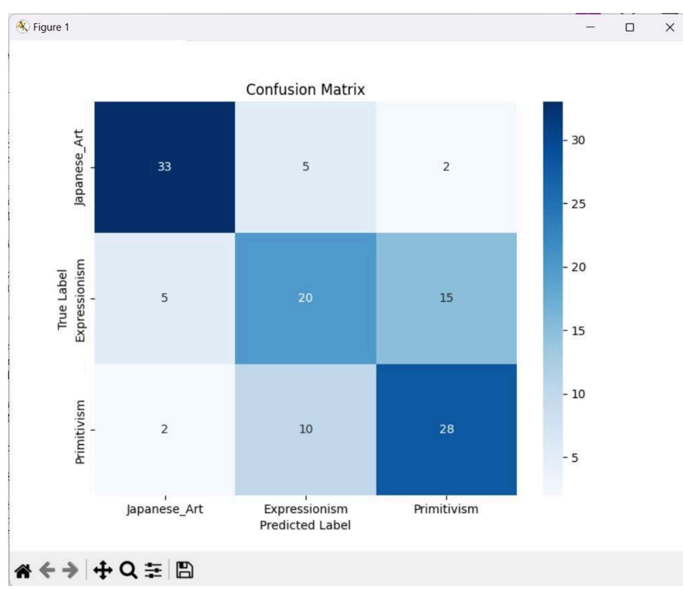

Fig. 4.2 Confusion Matrix

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V. RESULTS AND DISCUSSIONS

The project encapsulates the outcomes and insights gleaned from the implementation of the image classification model. This section serves as a comprehensive exploration of the model's performance, accuracy, and overall effectiveness in predicting art styles. It delves into the evaluation metrics, such as accuracy scores and confusion matrices, shedding light on the model's strengths and potential areas for improvement. Additionally, the discussion delves into the implications of the results, addressing the model's capability to generalize to unseen data and its robustness in handling diverse art styles. Through critical analysis, this section aims to provide a nuanced understanding of the image classification model's performance and its practical utility in real-world scenarios. The prediction of the image is based on the output of the trained machine learning model, which takes the input of various image categories such as Japanese Art, Expressionism, Primitivism etc. Image Classification Function is analyzed by all the input values with the SVM model created it will predict the image belongs to which class.

A. ROOT WINDOW

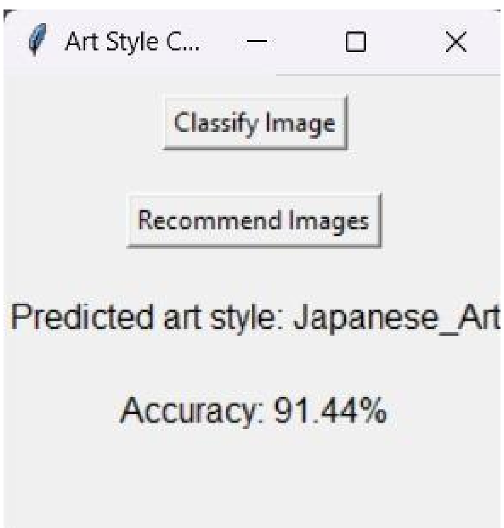

Fig. 5.1. Root Window

The root window of the GUI serves as the main interface for the Art Style Classifier application. This window, created using the Tkinter library, provides a user-friendly platform for interaction. It is titled "Art Style Classifier" and hosts essential components such as buttons and labels. The "Classify Image" button triggers the image classification process, prompting users to select an image for style prediction. The "Recommend Images" button suggests related images based on the predicted art style. Result labels dynamically display the predicted art style, and a separate label may indicate any recommendations or errors. Overall, the root window forms the central hub of the graphical user interface, facilitating user input and presenting the outcomes of the image classification and recommendation functionalities.

B. CLASSIFY IMAGE

The "Classify Image" button in the GUI (from Fig. 5.1) serves as the user-triggered mechanism to initiate the image classification process. When clicked, it prompts the user to select an image file from their device using the file dialog. The selected image is then loaded into the system, resized to a consistent format (150x150 pixels), and flattened to extract its pixel data. This preprocessed image data is then fed into the trained SVM (Support Vector Machine) model, which predicts the art style category of the image. The result label dynamically updates to display 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.

C. RECOMMEND IMAGES

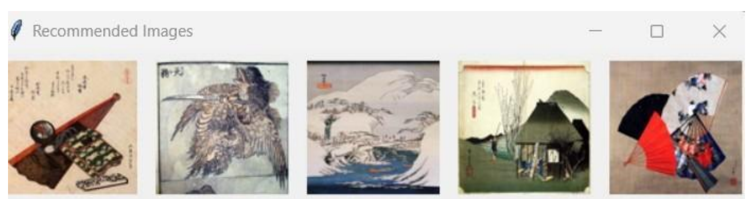

Fig. 5.2. Recommend Images

The "Recommend Images" button in the GUI initiates a functionality designed to provide users with additional suggestions based on the predicted art style of a classified image. Once the "Classify Image" button is utilized to predict the art style, the "Recommend Images" button comes into play. It first extracts the predicted art style from the result label. Subsequently, it identifies the corresponding folder in the dataset containing images of that predicted art style.The button then lists all files within the predicted art style folder and randomly selects up to five images for display. These images are presented in a separate window, offering users a visual recommendation related to the predicted art style. The functionality serves to enhance user engagement, allowing them to explore more examples of the predicted art style and appreciate the diversity within that category. The window automatically closes after five seconds to maintain a seamless user experience.

VI. CONCLUSION

In conclusion, the Art Style Classifier and Recommender System presents a comprehensive and user-friendly solution for exploring diverse art styles through image classification. The project successfully processes image data from various art categories, employing a Support Vector Machine (SVM) model for accurate classification. The Tkinter graphical user interface (GUI) enhances user interaction, allowing individuals to upload images and receive predictions for their respective art styles. The incorporation of model persistence using Pickle ensures efficiency by saving and loading the trained SVM model. The GUI dynamically updates information, displaying the predicted art style for classified images and offering users the option to explore additional recommendations from the same art style. The random selection of recommended images adds variety to the user experience. Looking forward, the project holds promising avenues for future enhancements, including the integration of deep learning models, real-time classification, and user feedback systems. Overall, the Art Style Classifier and Recommender System stands as an educational and exploratory tool, contributing to the realms of image classification, machine learning, and art appreciation. Its simplicity and functionality make it accessible and engaging for art enthusiasts and learners alike.

VII. FUTURE SCOPE

- Explore more advanced image classification models, such as deep learning architectures (e.g., Convolutional Neural Networks - CNNs). These models may capture more intricate patterns and features in images.
- Implement transfer learning by using pre-trained models like VGG, ResNet, or Inception. Fine-tune these models on your specific dataset to potentially improve classification accuracy.
- Use more efficient feature extraction techniques that reduce the dimensionality of the data while preserving important information. Techniques like Principal Component Analysis (PCA) or feature selection methods may help.
- Explore parallel processing capabilities offered by machine learning frameworks. Many frameworks support parallel processing on GPUs, which can lead to substantial speed improvements during training.
- If applicable, distribute the training process across multiple machines or nodes. This is particularly useful for large datasets and complex models.
- Extend the project to handle more art styles or classes. This would involve collecting and annotating a larger dataset with diverse art styles.
- Add user authentication to the application and provide personalized recommendations based on individual user preferences and history.
- Develop a mobile application version of the project to reach a wider audience. This would involve optimizing the application for mobile platforms and potentially integrating additional features.
- Implement a system that allows users to provide feedback on the classification results. Use this feedback to improve the model through continuous learning.

VIII. REFERENCES

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