SVM-powered Art Movement Identification

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***Abstract*— Art comes in many different types and styles, each with its special features and background. 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 main idea resides in the application of Support Vector Machines (SVM), a classification algorithm, to identify complex patterns within high-dimensional imagery data.**

Data augmentation techniques, enhance the diversity and quality of the dataset, enabling the model to generalize better across diverse artistic styles. The project uses grid search for hyperparameter tuning, optimizing the SVM model's performance. A graphical interface is used 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. 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 distinctions 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

The project uses machine learning, specifically Support Vector Machines (SVM) to classify different styles of art like Japanese art, Primitivism, and Expressionism. The objective is to develop a model capable of classifying artworks into distinct art movements, each possessing unique characteristics and cultural influences. Our dataset taken from Kaggle, is a compilation of images representing various art movements, such as 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 enhance the dataset, promoting better generalization across diverse artistic styles.

The dataset is then split into training and testing sets, and additional preprocessing steps are done. 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.

Predictions are made on the test set to assess the model's accuracy and performance. 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.

II. LITERATURE SURVEY

The research paper titled "Image Classification Using SVM and CNN," authored by Chaganti, Sai Yeshwanth, et al., introduces the utilization of Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) for image classification. They opted for a small-scale image classification approach. The initial phase involved the use of SVM with a limited dataset, resulting in 93% accuracy. The paper 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[1]. The publication was authored by Chandra, Mayank Arya, and S.K. regarding 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 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 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 complexities 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[3]. The 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. 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 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, explains 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 paper titled "SVM Active Learning Approach for Image Classification Using Spatial Information," authored by E. Pasolli and a team 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 examines 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[6]. The paper titled "Application of Pre-trained CNN for Image Classification" authored by Abdullah and M.S. Hasan, 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 how 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 paper titled "Road Vehicle Classification using Support Vector Machines," authored by Z. Chen and team, and presented at the \introduces an 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 paper titled "Image Classification via Support Vector Machine" by Xiaowu Sun and the team, explains the utilization of support vector machines (SVMs) for image classification. The paper highlights the efficiency of SVM as both a classification and regression algorithm[9]. The paper titled "Spatial and Structured SVM for Multilabel Image Classification" authored by S. Koda and team, 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[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 tumour 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 tumour 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 behavioural 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 graphical interface, offering a practical and interactive dimension to the classification system. Users can 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 enhancing 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 the 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 dataset and starts training and finding the accuracy.

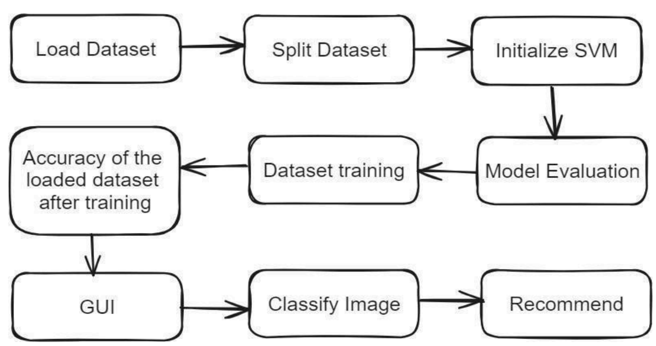

Fig. 3.1. End-to-end Pipeline

We start by loading our dataset, which comprises images categorized into different art styles, such as Japanese Art, Expressionism, and Primitivism. Each image is resized to a uniform dimension of 150x150 pixels to ensure consistency and then flattened into a one-dimensional array. This process simplifies the images while retaining their essential features, making them suitable for machine learning analysis. The flattened images along with their corresponding categories are stored in arrays, preparing the dataset for the next steps.

Once the dataset is prepared, it is split into training and testing sets using a 20% split ratio. This separation allows us 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 core of the project is the Support Vector Machine (SVM) model, which is initialized and then trained on the training set. SVM is chosen for its effectiveness in handling high-dimensional data and its capability to model complex boundaries between different classes. To find the best parameters for the SVM model, we employ GridSearchCV, which systematically works through multiple combinations of parameter tunes, cross-validating as it goes to determine which tune gives the best performance. After training, the model with the best parameters is selected.

Model evaluation is conducted by making predictions on the testing set and examining the results through a confusion matrix, which provides insights into the accuracy and areas of confusion (misclassifications) between different art styles. This evaluation step helps us understand the model's performance and its ability to correctly classify images into their respective art styles.

A graphical user interface (GUI) is developed using Tkinter, providing a user-friendly way to interact with the model. Through the GUI, users can upload images to be classified into an art style. The model predicts the art style of the uploaded image and displays the result along with the prediction's accuracy. Additionally, the GUI offers a feature to recommend images from the dataset that belong to the same art style as the classified image. This not only demonstrates the model's practical application but also enhances user engagement by allowing exploration of art styles through recommended images.

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 sophisticated dataset. This dataset encompassed a variety of art styles, deliberately chosen to cover a broad spectrum of visual characteristics. 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: In the data preprocessing phase, resizing and flattening images were pivotal steps, specifically choosing a uniform size of 150x150 pixels for all images. This size was selected to balance computational efficiency and the preservation of essential features necessary for the Support Vector Machine (SVM) model to effectively differentiate between art styles. The 150x150 resolution is manageable for processing, helping to reduce computational load while retaining sufficient detail in color, texture, and shape critical for recognizing nuanced differences in art movements like Japanese Art, Expressionism, and Primitivism. This dimension strikes a compromise between minimizing the risk of overfitting by not overwhelming the model with too much detail and ensuring enough data is available to avoid underfitting, facilitating consistent input format across the dataset. The choice reflects both empirical benchmarks and practical experience in image classification, optimizing the model’s performance by maintaining a balance between image quality and processing efficiency.

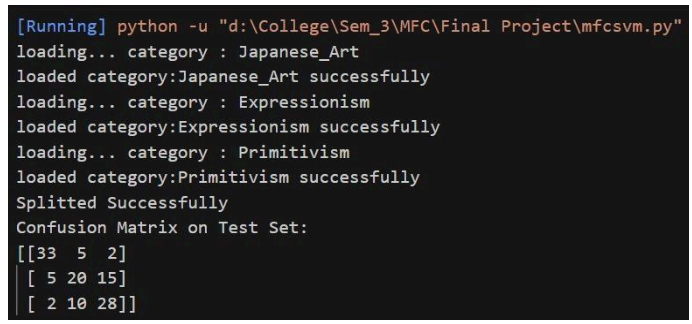

Fig. 4.1. Data Preprocessing

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.

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: After training the model, its performance was evaluated using a confusion matrix. This evaluation technique provides detailed insights into the model's classification accuracy across the different art styles. By comparing the predicted art styles against the true labels of the test set, the confusion matrix reveals not only the overall accuracy but also specific instances of misclassification. This evaluation step is crucial for understanding the model's strengths and weaknesses, enabling further refinement and adjustments to improve its accuracy. The confusion matrix was used to assess how well the SVM model could distinguish between the nuanced features of different art styles, such as Japanese Art, Expressionism, and Primitivism.

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.

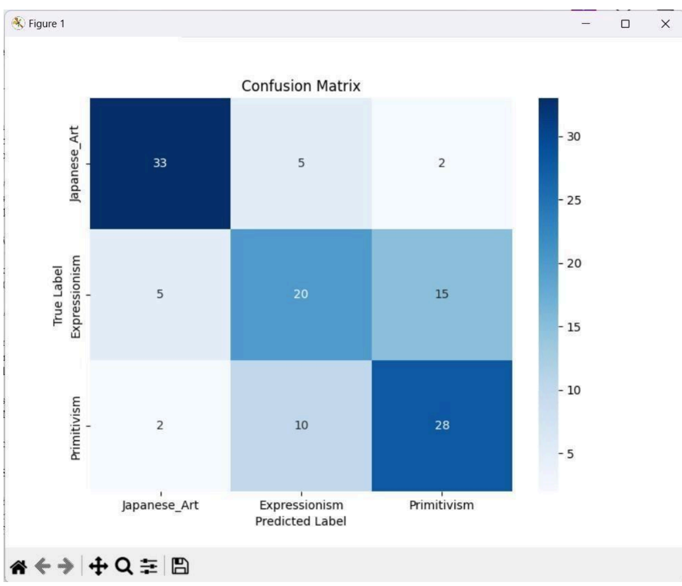

Fig. 4.2 Confusion Matrix

V. RESULTS AND DISCUSSIONS

The project summarizes the results and lessons learned from putting the image classification model into practice. This section serves as an exploration of the model's performance, accuracy, and overall effectiveness in predicting art styles. It explores 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 examines the implications of the results, addressing the model's capability to generalize to unseen data and its capability to handle diverse art styles. Through analysis, this section aims to provide an 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 dialogue. 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 resulting 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

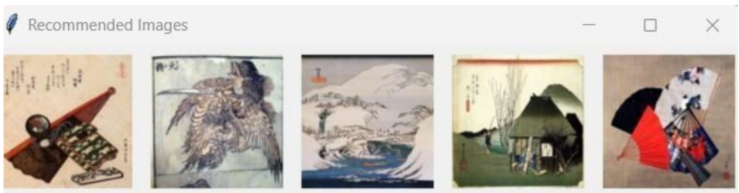

Fig. 5.2. Recommend Images

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. Moving ahead, the project offers exciting opportunities for improvements, such as adding deep learning methods, instant classification, and ways for users to give feedback. In essence, the Art Style Classifier and Recommender System serves as a learning and discovery resource in the fields of image classification, machine learning, and art enjoyment. Its straightforward design and practical features make it user-friendly and appealing for those interested in art.

VII. FUTURE SCOPE

To enhance the project, consider adopting more sophisticated image classification techniques like Convolutional Neural Networks (CNNs) for deeper insight into image patterns. Utilizing transfer learning with pre-trained models such as VGG, ResNet, or Inception could refine accuracy by adjusting them to your specific needs. Employing feature reduction methods like Principal Component Analysis (PCA) could streamline data while retaining crucial details. Leverage parallel processing and, if possible, distributed training across multiple devices to boost efficiency, especially with large datasets or complex models. Expanding the dataset to include a broader array of art styles, coupled with introducing user authentication for tailored recommendations, could enrich user experience. Developing a mobile app version would make the tool more accessible, and incorporating a feedback mechanism would allow for ongoing model improvement through user input.

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