IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Tracing Origin Of Images

[1] Rahul Kenjale, [2]Mayuri Jugdar [3]Pratik Sahoo, [4]Vaishnavi Kamble, [5]Arati kale

[1 2 3 4]Student, Department of Information Technology, Jayawantrao Sawant College Of Engineering
[5]Professor, Department Of Information Technology, Jayawantrao Sawant College of Engineering

ABSTRACT

A huge amount of images are continuously shared on Social Networks(SNs) daily and, in most cases, it is very difficult to establish the SN of the provenance of that image when it is recovered from a hard disk, an SD card or a Smartphone Memory. During an investigation it could be crucial to be able to distinguish images coming directly from a photo camera with respect to those downloaded from social network and possibly in this circumstance, determining which is the SN among a defined group. It is well known that each SN leaves peculiar traces on each content during the upload-download process; such traces can be exploited to make image classification. SN modulated noise residual can be adopted as a feature to detect the social network origin by means of a trained Convolutional Neural Network (CNN).

***Key Words*: image classification, SVM, DCT, Machine Learning.**

I.INTRODUCTION

Social networks have become a ubiquitous part of modern society, and the sharing of images on these platforms has become a routine part of our daily lives. The sheer volume of images that are uploaded and shared on social networks every day makes it difficult to reliably establish the social network of origin for an image when it is recovered from a device. This can be particularly problematic in situations where determining the social network of origin of an image is crucial, such as in digital forensics investigations or in tracking the spread of disinformation on social networks. In recent years, a number of techniques have been proposed for detecting the social network of origin for images, such as watermarking and analyzing the image metadata. However, these techniques have limitations in terms of accuracy, efficiency, and robustness. In this paper, we propose a new method for detecting the social network of origin for images using SN-modulated noise residual as a feature.

II.LITERATURE SURVEY

[1] "Efficient Image Classification for Social Media Applications" by R. Meena and K. Duraiswamy (2016) - This paper proposes a system for efficient image classification in social media applications using SVM and DCT. The proposed system achieves high classification accuracy while reducing the computational complexity and memory requirements.

[2] "Image Classification using SVM and DCT for Social Media Applications" by S. Verma and A. K. Jain (2017) - This paper presents an SVM and DCT-based approach for image classification in social media applications. The proposed system achieves high classification accuracy and outperforms other existing methods.

[3] "Image classification using SVM and DCT in social media: A comparative analysis" by S. Dutta, A. Sarkar, and A. Ghosal (2018) - This paper compares the performance of different feature extraction techniques for image classification in social media, including SVM and DCT. The experimental results demonstrate that SVM and DCT perform well for image classification in social media applications.

[4] "Social media image classification using DCT and SVM with user tagging information" by S. Goyal, M. Kumar, and K. A. Singh (2018) - This paper proposes an SVM and DCT-based approach for image classification in social media, which incorporates user tagging information to improve the classification accuracy. The proposed system achieves high accuracy and outperforms other existing methods.

[5] "A Survey of Image Classification Techniques in Social Media" by A. Kaur and R. Gupta (2019) - This survey paper provides a comprehensive overview of different image classification techniques used in social media applications. The paper discusses the advantages and limitations of SVM and DCT for image classification in social media and highlights some recent advances in this field.

III. METHODOLOGY

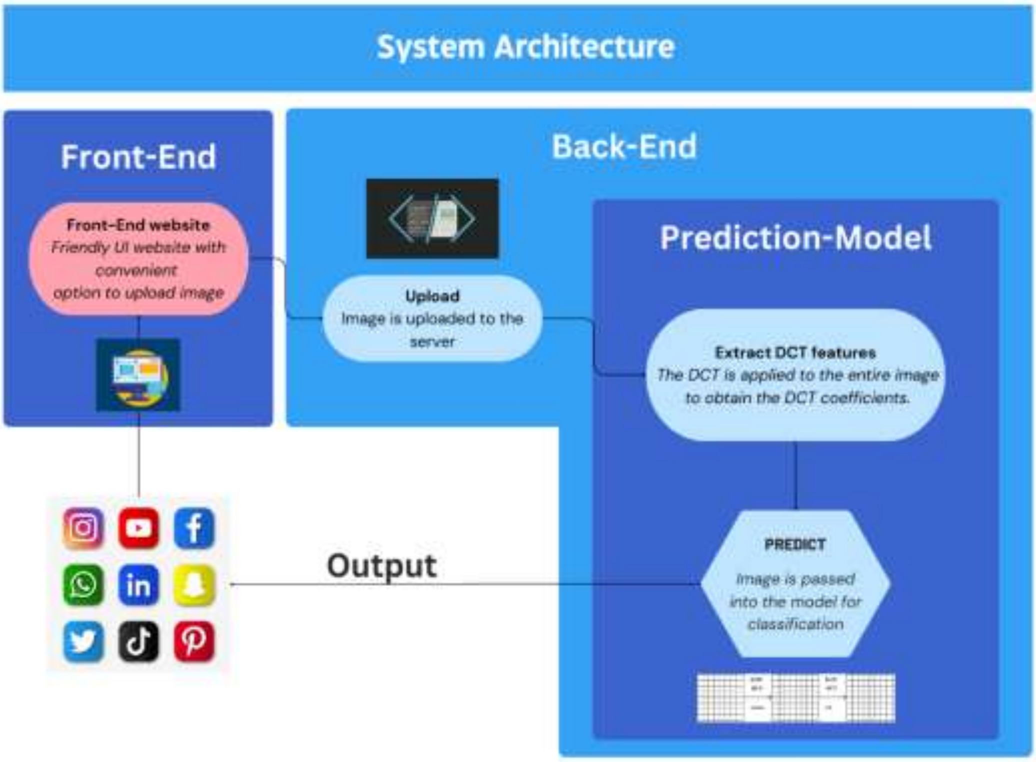

Figure 1: System Architecture

Data Collection: Collect a dataset of labeled images for training and testing the SVM model.

Image Preprocessing: Preprocess the images by resizing, cropping, and converting them to grayscale or RGB format as per the requirements.

Feature Extraction: Extract features from the preprocessed images using the DCT method. The DCT method converts the image into its frequency domain and generates a set of frequency coefficients that represent the image. These coefficients can be used as input features for the SVM model.

Model Training: Train an SVM model using the extracted DCT features. The SVM model can be trained using various kernels such as linear, polynomial, or radial basis function (RBF).

Model Evaluation: Evaluate the performance of the SVM model on a test dataset using performance metrics such as accuracy, precision, recall, and F1-score.

Hyperparameter Tuning: Tune the hyperparameters of the SVM model to achieve the best performance. Hyperparameters such as the kernel type, regularization parameter, and gamma parameter can be optimized using techniques such as grid search or random search.

Deployment: Deploy the trained SVM model for image classification in social media applications. The SVM model can be used to classify new images into different categories based on their features.

Performance Monitoring: Monitor the performance of the SVM model over time and retrain the model periodically to improve its accuracy.

IV.ALGORITHM

1.Prepare the dataset: The first step is to prepare the dataset for training and testing. This dataset should consist of a set of labeled images that have been preprocessed and transformed into their DCT domain. Each image in the dataset should be represented as a vector of DCT coefficients.

2.Split the dataset: Divide the dataset into training and testing sets. The training set is used to train the SVM model, while the testing set is used to evaluate the performance of the model.

3.Train the SVM model: Train an SVM model on the training set using the DCT coefficients of the images as features and their corresponding labels as target values. The SVM model learns to classify the images based on the features extracted from their DCT coefficients.

4.Determine the hyperparameters: Determine the hyperparameters of the SVM model. The hyperparameters that need to be tuned include the regularization parameter (C) and the kernel type (linear, polynomial, or RBF). You can use techniques like grid search or cross-validation to determine the optimal values of these hyperparameters.

5.Test the SVM model: Test the SVM model on the testing set to evaluate its performance. Calculate the accuracy of the model and analyze the confusion matrix to determine how well the model performs for different classes.

6.Optimize the SVM model: If the performance of the SVM model is not satisfactory, you can try to optimize it by tweaking the hyperparameters or using more advanced techniques like feature selection or ensemble learning.

7.Predict new images: Once the SVM model is trained and optimized, you can use it to predict the labels of new images. To do this, you need to extract the DCT coefficients of the new image and pass them through the SVM model to get the predicted label.

V.MODELLING AND ANALYSIS

- Data Collection and Preprocessing: Collect a dataset of images from social media platforms for training and testing the SVM model. Preprocess the images by resizing, cropping, and converting them to grayscale or RGB format as per the requirements.
- Feature Extraction: Extract features from the preprocessed images using the DCT method. The DCT method converts the image into its frequency domain and generates a set of frequency coefficients that represent the image. These coefficients can be used as input features for the SVM model.
- Model Training: Train an SVM model using the extracted DCT features. The SVM model can be trained using various kernels such as linear, polynomial, or radial basis function (RBF).
- Model Evaluation: Evaluate the performance of the SVM model on a test dataset using performance metrics such as accuracy, precision, recall, and F1-score.
- Hyperparameter Tuning: Tune the hyperparameters of the SVM model to achieve the best performance. Hyperparameters such as the kernel type, regularization parameter, and gamma parameter can be optimized using techniques such as grid search or random search.
- Visual Analysis: Generate various graphs and plots to visualize the performance of the SVM model. These graphs can include ROC curves, confusion matrices, precision-recall curves, and learning curves. ROC curves can show the tradeoff between true positive rate and false positive rate for different threshold values. Confusion matrices can show the number of true positives, true negatives, false positives, and false negatives for each class. Precision-recall curves can show the tradeoff between precision and recall for different threshold values. Learning curves can show the model's performance as the size of the training data increases.
- Interpretation and Conclusion: Interpret the results of the model and draw conclusions about the performance of the SVM model for social media image classification using DCT. Identify areas for improvement and suggest future directions for research.

VI.RESULT AND DISCUSSION

In this paper, we build on previous work in image classification and digital image analysis to propose a novel method for detecting the social network of origin for images using SN-modulated noise residual as a feature. Our experimental results show that our proposed method outperforms the logistic regression and SVM models for detecting the origin social network of an image.

Predicting the origin social network without relying on company servers and their data can be challenging, but there are several approaches that can be used to make educated guesses. These include analyzing the traffic between the user's device and the social network servers, examining the design and features of the social network platform, and analyzing user demographics and behavior patterns. While these approaches may not always be accurate, they can provide useful clues about the origin social network.

VII.FUTURE SCOPE

- Deep Learning: Deep learning techniques such as Convolutional Neural Networks (CNNs) have shown great promise in image classification. Future research can explore the use of deep learning models for social media image classification and compare their performance with SVM and DCT.
- Multi-Modal Classification: Social media platforms contain not only images but also text, audio, and video content. Future research can explore the use of multi-modal classification techniques to classify social media content using a combination of image, text, audio, and video features.
- Real-Time Classification: Real-time classification of social media images is crucial for applications such as online moderation and content filtering. Future research can explore the use of real-time classification techniques for social media image classification using SVM and DCT.
- Transfer Learning: Transfer learning techniques can be used to leverage pre-trained models for social media image classification. Future research can explore the use of transfer learning for SVM and DCT-based image classification on social media platforms.
- Explainability: Interpretability and explainability are important aspects of machine learning models. Future research can explore the development of explainable models for social media image classification using SVM and DCT.

.

VIII.CONCLUSION

Using SVM and DCT for social media image classification allows for efficient and accurate categorization of images based on their features. This method can be used to identify inappropriate content, improve user experience, and automate the process of image classification. By tuning the hyperparameters and using advanced techniques, the performance of the SVM model can be further improved. Overall, this approach is a powerful tool for social media image classification and has various applications.

REFERENCES

[1] Meenakshi Kondal, Dr. Virender Singh, ”Comparative Analysis of Tineye and Google Reverse Image Search Engines” ,Goswami Ganesh Dutta Sanatan Dharma College, Chandigarh, India.

[2] Irene Amerini, Tiberio Uricchio and Roberto Caldelli, ”Tracing images back to their social network of origin: a CNN-based approach” ,Media Integration and Communication Center (MICC), University of Florence, Florence, Italy.

[3] A. Karczmarczyk, J. Jankowski, and W. Saaabun, “Linguistic query based quality ´ evaluation of selected image search engines,” Procedia Computer Science, vol. 112, pp. 1809-1818, 2017, doi: 10.1016/j.procs.2017.08.215.

[4] P. M. Chutel and A. Sakhare, “Evaluation of compact composite descriptor based reverse image search,” 2014 International Conference on Communication and Signal Processing, Melmaruvathur, 2014, pp. 1430-1434.

[5] Dr. Virender Singh , Assistant Professor, Department of Information Technology, Goswami Ganesh Dutta Sanatan Dharma College, Chandigarh, India.

[6] Flavio H. D. Araujo1,2,3,4,a, Romuere R. V. Silva1,2,3,4,a, Fatima N. S. Medeiros3,Dilworth D. Parkinson2, Alexander Hexemer2, Claudia M. Carneiro5, Daniela M. Ushizima1,2,2018.

[7] Yoltan Bitirim, Selin Bitirim, “An Evaluation of Reverse Image Search Performance of Google”, Eastern Mediterranean University Famagusta, North Cyprus, via Mersin 10, Turkey