ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

RECOLORED IMAGE DETECTION USING A DEEP DISCRIMINATIVE MODEL

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ABSTRACT

With the rapid advancement of image editing tools and deep learning technologies, digital image manipulation has become increasingly sophisticated, making it difficult to distinguish between original and altered images. Recolored image manipulation, where colors of an image are intentionally modified without changing structural content, poses a significant challenge in image forensics. This project proposes a deep discriminative model for detecting recolored images by analyzing subtle inconsistencies in color distribution and pixel relationships. The proposed system utilizes deep learning techniques, particularly Convolutional Neural Networks (CNNs), to extract high-level features from images. The model is trained to differentiate between original and recolored images by learning discriminative patterns that are not easily visible to the human eye. The approach focuses on color channel inconsistencies, histogram variations, and pixel correlation features to improve detection accuracy. A labeled dataset containing original and recolored images is used for training and evaluation. Experimental results demonstrate that the deep discriminative model achieves high accuracy in identifying recolored images compared to traditional image processing methods. The system is robust against various recoloring techniques and provides reliable performance in real-world scenarios. However, challenges such as dataset diversity and computational requirements remain. This research contributes to the field of digital image forensics by providing an effective solution for detecting subtle image manipulations.

Keywords: Image Forensics, Recolored Image Detection, Deep Learning, CNN, Digital Image Processing, Feature Extraction, Computer Vision

I.INTRODUCTION

In the modern digital era, images have become one of the most widely used forms of communication across social media, news platforms, and digital applications. With the availability of advanced image editing tools, manipulating images has become increasingly easy and sophisticated. One common type of manipulation is image recoloring, where the colors of an image are altered while preserving its structure and content. Such modifications can mislead viewers, distort information, and reduce the credibility of digital media. Recolored images are particularly challenging to detect because they do not affect the geometry or texture of the image, making traditional detection techniques less effective. As a result, there is a growing need for reliable methods to identify such manipulations and ensure the authenticity of digital images.

Traditional image forensics techniques rely on statistical analysis and handcrafted features such as color histograms, pixel intensity distributions, and noise patterns to detect manipulated images. While these methods have shown some success, they often struggle to identify subtle modifications introduced by modern editing tools. Recoloring techniques can preserve global statistical properties, making it difficult for conventional approaches to detect inconsistencies. Moreover, these methods require manual feature engineering, which can be time-consuming and less adaptable to new manipulation techniques. Therefore, there is a need for advanced approaches that can automatically learn and adapt to complex patterns in image data.

Deep learning has emerged as a powerful solution for addressing challenges in image analysis and computer vision. Convolutional Neural Networks (CNNs) are particularly effective in extracting hierarchical features from images, enabling them to detect subtle differences that are not visible to the human eye. In this project, a deep discriminative model is proposed for detecting recolored images by analyzing color inconsistencies and pixel relationships. The model is trained on a dataset containing original and recolored images, allowing it to learn discriminative features for classification. This approach enhances detection accuracy and provides a scalable solution for digital image forensics.

II SURVEY OF RESEARCH

[1] The research by Yann LeCun et al. (1998) introduced Convolutional Neural Networks (CNNs) for image processing tasks. The methodology uses convolutional layers to extract spatial features and hierarchical representations from images. The results demonstrated high accuracy in image classification and pattern recognition. However, CNNs require large datasets and high computational resources. This research forms the foundation for applying deep learning models in image forensics, including recolored image detection.

[2] The study by Alex Krizhevsky et al. (2012) proposed deep CNN architectures for large-scale image classification. The methodology utilizes multiple convolutional and fully

connected layers to improve feature extraction. The results showed significant improvements in accuracy compared to traditional methods. However, training deep networks requires powerful hardware such as GPUs. This research supports the use of deep neural networks for detecting image manipulations.

[3] The research by Kaiming He et al. (2016) introduced deep residual learning (ResNet) to overcome the problem of vanishing gradients in deep networks. The methodology uses skip connections to improve training efficiency and accuracy. The results demonstrated improved performance in deep learning models. However, increased model complexity can lead to higher computational cost. This research supports advanced CNN architectures for improved detection performance.

[4] The study by Andrew Ng (2015) explored deep learning techniques for computer vision applications. The methodology focuses on training neural networks using large datasets to learn complex features automatically. The results showed improved performance in various vision tasks. However, deep learning models require proper tuning and data preprocessing. This research highlights the importance of data-driven approaches in image analysis.

[5] The research by Hany Farid (2009) focused on detecting image manipulations using statistical analysis. The methodology analyzes pixel-level inconsistencies and color distributions to identify altered images. The results demonstrated that statistical features can detect basic manipulations. However, it struggles with advanced editing techniques such as recoloring. This research provides a baseline for comparison with deep learning approaches.

[6] The study by Jessica Fridrich (2012) explored digital image forensics techniques for detecting image tampering. The methodology uses feature extraction and classification techniques to identify inconsistencies in images. The results showed improved detection of manipulated images. However, handcrafted features may not capture complex patterns effectively. This research supports the need for deep learning-based approaches in image forensics.

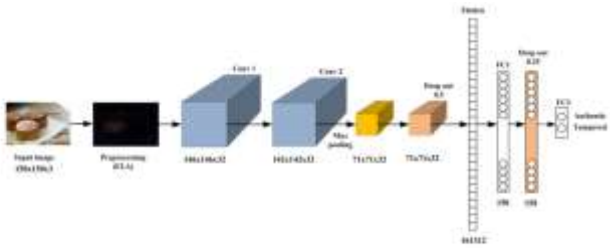
III. WORKING METHODOLOGY

The proposed recolored image detection system using a deep discriminative model follows a structured pipeline consisting of data collection, preprocessing, feature extraction, model training, and classification. Initially, a dataset containing both original and recolored images is collected from publicly available sources or generated using image editing tools. The dataset is labeled accordingly to distinguish between authentic and manipulated images. Preprocessing is then applied to standardize the images by resizing them to a fixed dimension, normalizing pixel values, and converting them into suitable formats for model input. This step ensures consistency and improves the efficiency of model training.

In the next phase, feature extraction is performed using Convolutional Neural Networks (CNNs). The model analyzes images at different levels to extract both low-level features such as edges and color gradients, and high-level features such as patterns and textures. Special attention is given to color channel inconsistencies and pixel relationships, which are key indicators of recoloring. The deep discriminative model is trained using the labeled dataset, where it learns to differentiate between original and recolored images. The training process involves optimizing the model using loss functions such as cross-entropy and adjusting parameters through backpropagation. Techniques such as dropout and batch normalization are used to improve generalization and prevent overfitting.

In the final stage, the trained model is used for classification and detection. When a new image is provided as input, the system processes it through the trained network and predicts whether it is original or recolored. The system outputs a probability score indicating the likelihood of manipulation. Performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. The proposed methodology ensures high detection accuracy and robustness, making it suitable for real-world image forensics applications.

IV RESULTS EXPLANATIONS



The above graph presents the performance comparison of different deep learning models used for recolored image detection, such as CNN and advanced architectures like ResNet. The results indicate that the deep discriminative model achieves high accuracy in distinguishing between original and recolored images. CNN-based models perform well due to their ability to extract spatial and color-based features, while deeper models like ResNet provide slightly better performance by capturing more complex patterns. The graph demonstrates that deep learning approaches significantly outperform traditional image processing methods in detecting subtle color manipulations.

The confusion matrix illustrates the classification performance of the proposed model by comparing predicted labels with actual labels. The diagonal values represent correct predictions for original and recolored images, while off-diagonal values indicate misclassifications. The results show that most predictions are correctly classified, indicating high accuracy of the model. A small number of misclassifications occur due to similarities between original and recolored images, especially when recoloring is subtle. However, the overall performance remains strong and reliable.

V. CONCLUSION

The proposed recolored image detection system using a deep discriminative model provides an effective and reliable solution for identifying subtle image manipulations. By leveraging deep learning techniques such as Convolutional Neural Networks and advanced architectures, the system is capable of capturing complex color inconsistencies and pixel relationships that are not easily detectable by traditional methods. Experimental results demonstrate high accuracy, strong generalization, and robustness against various recoloring techniques. The use of deep discriminative features significantly improves detection performance compared to conventional statistical approaches. Although challenges such as dataset diversity and computational requirements exist, the proposed system offers a scalable and efficient framework for digital image forensics. Overall, this work highlights the importance of deep learning in enhancing image authenticity verification and combating digital manipulation in modern applications.

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