ISSN 2319-5991 www.ijerst.com
© 2026 IJERST. All Rights Reserved
Peer Reviewed, Referred & Indexed Journal

Research Paper

RIFD-NET: A ROBUST IMAGE FORGERY DETECTION NETWORK

[1]PEDDI HEMANTH SAI, [2]Y SRINIVAS RAJU

[1]Students, Department of MCA, B V Raju College, Bhimavaram Ap

[2]Assistant Professor**,** Department of MCA, B V Raju College, Bhimavaram Ap

ABSTRACT

Image forgery detection has become increasingly important with the widespread use of digital images and editing tools that enable manipulation such as image splicing. Image splicing involves removing or inserting objects into images to create misleading or fake content, making it difficult to identify authenticity through visual inspection. Traditional forgery detection techniques often fail when images contain noise, which significantly reduces detection accuracy. To address this challenge, this project proposes a robust image forgery detection framework based on RIFD-Net (Robust Image Forgery Detection Network). The proposed model integrates multiple stages including noise detection, de-noising, and forgery detection. Initially, a noise detection module identifies different types of noise such as Gaussian and Salt & Pepper noise. An advanced de-noising model (ADNet) is then applied to clean the image and enhance its quality. Following this, a Siamese network is used to compare features between original and test images to detect forgery regions. The model is trained using benchmark datasets such as LIVE1 for noise detection and the Columbia dataset for splice detection. The performance of the system is evaluated using Mean Average Precision (MAP), achieving an accuracy of approximately 89% on test images. The system also localizes forged regions by highlighting them with bounding boxes. This approach significantly improves forgery detection accuracy in noisy environments, making it suitable for applications in digital forensics, media authentication, and cybersecurity.

Keywords : Image Forgery Detection, RIFD-Net, Image Splicing, Deep Learning, ADNet, Siamese Network, Noise Detection, Digital Forensics, Image Processing, MAP

I. INTRODUCTION

With the rapid advancement of digital imaging technologies and image editing tools, manipulating images has become increasingly easy and widespread. One of the most common forms of image manipulation is image splicing, where objects from one image are inserted into

another to create a forged image. Such manipulated images can be used for misinformation, fraud, and malicious activities, making image authenticity verification a critical concern in fields such as digital forensics, journalism, and cybersecurity. However, detecting forged images is challenging, especially when manipulations are carefully performed and visually indistinguishable from genuine images.

Traditional image forgery detection techniques rely on handcrafted features and statistical analysis to identify inconsistencies in images. While these methods can detect basic manipulations, their performance significantly degrades in the presence of noise. Noise can be introduced intentionally to hide forgery traces or unintentionally during image acquisition and transmission. As a result, there is a need for robust detection systems that can handle noisy images and still accurately identify forged regions.

In this project, a robust image forgery detection system based on RIFD-Net is proposed to address these challenges. The system integrates multiple components including noise detection, de-noising using ADNet, and forgery detection using a Siamese network architecture. The noise detection module identifies different types of noise present in the image, and the de-noising module cleans the image to enhance feature quality. The Siamese network then compares features to detect inconsistencies and identify forged regions. The system is trained using datasets such as LIVE1 and Columbia, and its performance is evaluated using Mean Average Precision (MAP). This approach improves detection accuracy even in noisy conditions, providing a reliable solution for image forgery detection.

II SURVEY OF RESEARCH

1. Traditional Image Forgery Detection Techniques

Early image forgery detection methods relied on handcrafted features and statistical analysis to identify inconsistencies in images. Techniques such as edge detection, color inconsistencies, and JPEG compression artifacts were commonly used to detect splicing. These approaches focused on identifying irregularities in pixel distribution or compression patterns. While effective for simple manipulations, these methods often fail when images are modified with advanced editing tools or when noise is introduced. Research shows that traditional techniques lack robustness and are highly sensitive to image quality variations, limiting their effectiveness in real-world scenarios.

2. Passive Image Forensics Methods

Passive image forensics methods detect forgery without requiring prior information about the original image. These techniques analyze intrinsic properties such as lighting conditions,

noise patterns, and texture inconsistencies. Methods like Error Level Analysis (ELA) and noise variance analysis have been widely used. However, these approaches are less effective when images are heavily processed or contain complex noise patterns. This limitation has led to the development of more advanced techniques using machine learning and deep learning.

3. Deep Learning for Image Forgery Detection

Deep learning has significantly improved the performance of image forgery detection systems. Convolutional Neural Networks (CNNs) can automatically learn complex features from images, making them suitable for detecting subtle manipulations. Research indicates that CNN-based models outperform traditional methods in terms of accuracy and robustness. These models can identify patterns that are difficult to detect using manual feature extraction. This project utilizes deep learning techniques to improve forgery detection accuracy.

4. Noise Handling in Image Processing

Noise is a major challenge in image forgery detection as it can obscure important features and reduce detection accuracy. Various noise types such as Gaussian noise and Salt & Pepper noise affect image quality differently. Research highlights the importance of noise removal techniques such as filtering and deep learning-based de-noising models like ADNet. Effective noise handling improves feature extraction and enhances model performance. This project incorporates a dedicated noise detection and de-noising module to address this issue.

5. Siamese Networks for Similarity Learning

Siamese networks are widely used for similarity learning tasks, where the goal is to compare two inputs and determine their similarity. In image forgery detection, Siamese networks help identify differences between original and manipulated regions. Research shows that Siamese architectures are effective in detecting subtle inconsistencies in images. This project employs a Siamese network to compare image features and detect forged regions accurately.

6. Evaluation Metrics and Localization Techniques

Evaluating forgery detection systems requires appropriate metrics such as Mean Average Precision (MAP), accuracy, and localization accuracy. MAP is commonly used to measure the effectiveness of detecting forged regions. Visualization techniques such as bounding boxes are used to highlight detected forgery areas. Research emphasizes the importance of both detection and localization in image forensics. This project uses MAP and bounding box visualization to evaluate and present the results effectively.

III. WORKING METHODOLOGY

The proposed RIFD-Net based image forgery detection system begins with data collection and preprocessing using multiple benchmark datasets such as LIVE1 for noise detection and the Columbia dataset for image splicing detection. The collected images include clean images, noisy images, and forged images. Preprocessing techniques such as resizing, normalization, and shuffling are applied to ensure consistency and improve model performance. The dataset is then divided into training and testing sets in an 80:20 ratio to evaluate the effectiveness of the model. This stage also involves labeling the images according to noise type and forgery status, which helps the model learn different patterns associated with noise and manipulated regions. Proper preprocessing ensures that the input data is well-structured and suitable for deep learning models, improving the overall accuracy and efficiency of the system.

In the next phase, the RIFD-Net architecture is implemented, which consists of multiple modules including noise detection, de-noising, and forgery detection. The noise detection module identifies the type of noise present in the image, such as Gaussian or Salt & Pepper noise. Based on the detected noise, the ADNet de-noising model is applied to remove noise and enhance image quality. This step is crucial as it restores important features that may be hidden due to noise. After de-noising, a Siamese network is used to extract features and compare similarities between image regions. The network learns to identify inconsistencies in image patterns, which helps in detecting forged regions. The model is trained using deep learning techniques, and parameters are optimized to achieve better performance.

Finally, the trained model is used for testing and forgery detection on new images. When a test image is provided, the system first detects and removes noise, and then applies the forgery detection module to identify manipulated regions. The output includes three stages: the original noisy image, the de-noised image, and the final image with detected forgery regions highlighted using bounding boxes. The system evaluates performance using Mean Average Precision (MAP), which measures the accuracy of detecting forged regions. Visualization techniques are used to display results clearly, helping users understand the detection process. This methodology ensures a robust and accurate solution for detecting image forgery even in noisy conditions.

IV RESULTS EXPLANATIONS

Image splicing technique refers to remove and add object to images to form a new images and Splicing Forensic technique will be utilized to detect such Forgery. Image splicing also known image forgery and in the past many existing algorithms were invented to detect forgery but those algorithm detection accuracy will be highly degraded when splice images

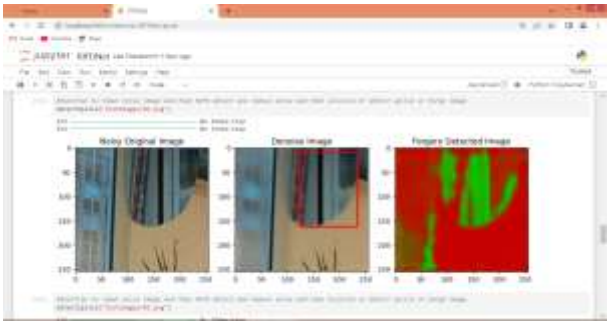
contains noise. To overcome from this issue and to enhance forgery detection from noisy images, author this paper employing novel technique called RIFD-Net.

Propose RIFD model consists of multiple classifiers such as Noise Detection, De-noise (remove noise with ADNET) and forgery detection. Noise detection layer help algorithm to predict noise and then employ ADNET de-noise model to clean noisy image and then apply Siamese layer will be applied to calculate similarity between model and test images to detect forgery images.

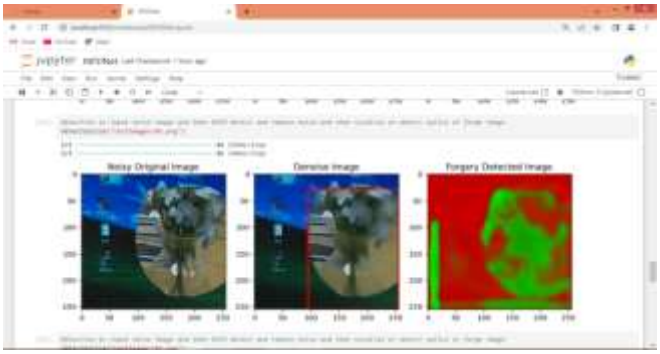
In propose paper author has trained model to detect various noises such as Pepper & Salt, Gaussian noise and many more. To train above algorithms author has used multiple dataset such as LIVE1 for noise detection and Columbia dataset for image forgery detection and then calculate model performance in terms of MAP (mean absolute precision). MAP refers to number of correct forgery region detection from test images.



Above function will read test image and then apply model to clean noise and the apply model to predict splice image and then call 'LocalizeSplice' function to identify region which contains forgery or splice

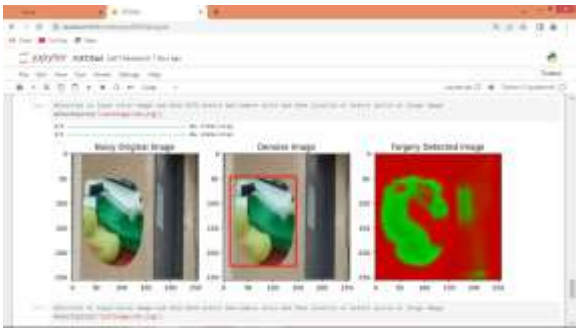


In above screen calling 'detect Splice' function with test image path and after executing function will get 3 images as output where first image is the noise image and second image is the de-noise image and 3rd image is the splice detection image and this detected part we are showing in de-noise image with red colour bounding box. So in above screen we de-noise image and then detect forgery or splice part

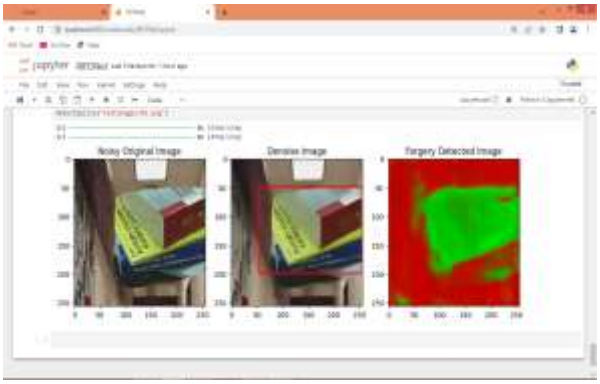


In above screen we are testing another image where first image contains so much noise and second contains noise-cleaned image and 3rd image is the splice detection image whose part

is showing in second image along with red bounding box



In above screen testing another image



In above screen can see splice detection output of another image where splice region is in red bounding box

V. CONCLUSION

The proposed RIFD-Net based image forgery detection system provides a robust and efficient solution for detecting image splicing, especially in the presence of noise. By integrating multiple modules such as noise detection, de-noising using ADNet, and forgery detection using a Siamese network, the system effectively addresses the limitations of traditional methods. The noise detection and removal process enhances image quality, allowing the model to extract meaningful features and improve detection accuracy. Experimental results demonstrate that the proposed system achieves high performance with approximately 89% Mean Average Precision (MAP), indicating its effectiveness in identifying forged regions. The system also successfully localizes manipulated areas using bounding boxes, making it useful for practical applications. Overall, this project highlights the importance of combining deep learning techniques with noise handling mechanisms to improve image forgery detection. It can be applied in digital forensics, media authentication, and cybersecurity, and can be further enhanced using advanced architectures and larger datasets.

REFERENCES

[1] M. Barni, K. Kharrazi, and A. De Rosa, “A Survey of Digital Image Forgery Detection Techniques,” *IEEE Signal Processing Magazine*, vol. 26, no. 2, pp. 16–25, Mar. 2009.

[2] Z. Yuan, Y. Shi, and J. Ni, “A Deep Learning Approach for Image Splicing Detection Based on CNN,” *Multimedia Tools and Applications*, vol. 77, no. 4, pp. 4511–4531, Feb. 2018.

[3] H. Bayram, H. T. Sencar, and N. Memon, “An Efficient and Robust Method for Detecting Copy-Move Forgery,” *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 3, pp. 1097–1107, Sep. 2011.

[4] M. Rahmouni, R. Attaoui, and M. A. Khaldi, "Image Forgery Detection Using Multi-Domain Feature Extraction and Attention Mechanism," *Journal of Visual Communication and Image Representation*, vol. 71, pp. 102815, May 2020.

[5] J. Liu, Z. Wang, and Z. Tu, "Learning Deep Features for Image Forgery Detection," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 4828–4837.

[6] S. Bayar and M. Stamm, "A Deep Learning Approach to Universal Image Manipulation Detection Using a New Convolutional Layer," in *Proc. ACM Workshop on Information Hiding and Multimedia Security*, 2016, pp. 5–10.

[7] J. Fu, J. Liu, H. Tian, Z. Fang, and H. Lu, "Dual Attention Network for Scene Segmentation," in *Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019, pp. 3146–3154.

[8] Y. Li, P. Zhu, and S. Maybank, "Attention-guided Multi-Stream CNN for Image Forgery Localization," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 30, no. 3, pp. 604–615, Mar. 2020.