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A Hybrid Approach to Image Forgery Detection Using OpenCV, MD5, SHA-256, Blowfish & SSIM

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ABSTRACT: In an era where digital documents are highly vulnerable to manipulation, ensuring robust forgery detection mechanisms is crucial. This project presents a comprehensive approach to detecting tampering in document images using image processing techniques. It incorporates four distinct algorithms — MD5 hashing, SHA-256 hashing, Blowfish encryption, and Structural Similarity Index (SSIM) analysis to assess image integrity. A user-friendly interface built with PyQt5 allows users to upload two images for comparison, where the system identifies and highlights tampered areas. Users can choose one of the three detection methods, with MD5 and SHA-256 generating cryptographic hashes for quick integrity checks, while SSIM detects subtle modifications by evaluating structural differences. The image processing pipeline includes pre-processing steps such as resizing and grayscale conversion, followed by hash value generation and structural similarity score calculation. Discrepancies are visually represented using bounding boxes to enhance clarity in tampering detection. Experimental results validate the effectiveness of this approach in identifying various types of tampering, making it a reliable tool for document verification across legal, academic, and financial sectors. This study highlights the significance of integrating image processing techniques to strengthen digital document security and integrity in an increasingly digitalized world.

KEYWORDS: Document forgery detection, image processing, MD5, SHA-256, Structural Similarity Index, PyQt5.

I. INTRODUCTION

In the digital age, the proliferation of information has led to the widespread use of digital documents for various applications, including legal contracts, academic submissions, financial statements, and personal communications. As these documents are often shared, edited, and stored electronically, the potential for unauthorized alterations and forgery has significantly increased. The consequences of such tampering can be severe, ranging from financial loss and legal disputes to damage of reputation and trust. Thus, the need for effective and reliable forgery detection mechanisms has become critical in ensuring the authenticity and integrity of digital documents.

Blowfish Encryption: Alongside hashing techniques, Blowfish, a symmetric-key block cipher, is incorporated for encryption-based verification. Blowfish offers fast and secure encryption, allowing an additional layer of integrity check by encrypting the document image and comparing decrypted outputs for alterations.

Document forgery can take various forms, including the manipulation of text, images, or even entire pages. With the advancement of image editing tools and software, detecting tampering in documents has become increasingly challenging, necessitating the development of sophisticated detection techniques. Traditional methods, such as visual inspection, are often insufficient due to their subjective nature and the technical skills required to identify subtle manipulations. Therefore, there is a strong need for automated systems that can efficiently and accurately identify forged documents.

This research project aims to address these challenges by implementing a robust image forgery detection system utilizing image processing techniques. The focus of our approach is on detecting tampered areas within document images by employing three distinct algorithms: MD5 hashing, SHA-256 hashing, and Structural Similarity Index (SSIM). Each of these methods offers unique benefits and effectiveness in identifying alterations, providing a comprehensive analysis of document integrity.

1. **MD5 and SHA-256 Hashing**: These cryptographic hash functions are designed to produce fixed-size hash values from the input data. In our framework, the original document image and the suspected modified image are transformed into their respective hash values. An identical hash indicates that the documents have not been altered; however, a discrepancy highlights potential tampering. While MD5 is faster and commonly utilized, SHA-256 offers greater security and resistance to collision attacks, making it a critical component of our forgery detection system.
2. **Structural Similarity Index (SSIM)**: This technique goes beyond simple hash comparisons by quantifying the perceived difference between two similar images. SSIM considers changes in structural information, luminance, and contrast, making it a powerful tool for identifying subtle alterations that hashing alone might overlook. By detecting spatial and tonal differences, SSIM can reliably indicate regions of an image that have been manipulated.
3. **User Interface and Workflow**: To facilitate user interaction with our detection system, we built a

graphical user interface (GUI) using PyQt5. This interface allows users to upload two images for comparison – the original and the suspected tampered version. Users can select the detection method of their choice, and the system will visually highlight any detected tampered areas.

The significance of this research lies in its potential applications across various fields. In legal settings, it could help verify the authenticity of contracts and agreements. In academia, it can be employed to ensure the integrity of submitted works and research. Financial institutions could utilize this technology to authenticate transaction records and statements.

In conclusion, our work addresses the critical necessity for automated detection of document forgery through the integration of advanced image processing techniques. By employing a combination of hashing and structural analysis methods, we aim to create a comprehensive and user-friendly system that enhances document security and trust in the digital landscape.

II. LITERATURE SURVEY:

In the pursuit of advancing forgery detection techniques in digital images, several key studies have contributed to the understanding and implementation of various methods. This literature survey critically evaluates the findings from notable research papers in state-of-the-art technologies for image forgery detection, focusing on image splicing and image manipulation methodologies.

Xiao et al. [1] proposed a robust method for image splicing forgery detection that combines coarse-to-refined convolutional neural networks (CNNs) with adaptive clustering techniques. Their study highlights the advantages of using a deep learning framework which enhances the accuracy of detecting manipulated images by progressively refining the feature extraction process. Despite its effectiveness, the reliance on substantial labeled training data may pose a limitation in scenarios where such data is scarce.

Zheng et al. [2] conducted a comprehensive survey on image tampering detection in real-world photographs, discussing various techniques and challenges associated with detecting manipulated images. Their work systematically categorizes existing detection methods, emphasizing the necessity for adaptive approaches that can address the dynamic nature of image manipulation techniques. This survey serves as a valuable resource for understanding historical and modern trends in tampering detection.

Kwon et al. [3] introduced the CAT-Net, a specialized convolutional neural network designed to trace compression artifacts, thereby aiding in the detection and localization of image splicing. Their approach utilizes deep learning to exploit the inherent artifacts created during the compression of images, demonstrating a high capability for accurately identifying and highlighting tampered areas. Nonetheless, the application of this method may be limited in cases where no compression artifacts are present or detectable.

comprise image pre-processing, hash generation, tampering detection using multiple methods (MD5, SHA-256, and Structural Similarity Index), and the user interface.

Bondi et al. [4] made significant strides toward camera model identification using Convolutional Neural Networks (CNNs). Their research illustrates how CNNs can be utilized to differentiate between images captured by different camera models, laying the groundwork for further forensic analysis. While their findings are promising, the implementation in real-world scenarios may require extensive databases of known camera characteristics for effective training.

Bayar and Stamm [5] focused on universal image manipulation detection through a novel convolutional layer designed to enhance detection capabilities in various image manipulation scenarios. They provided evidence of the layer's effectiveness in identifying numerous types of image alterations, although the need for a diverse dataset during training is essential to achieve high accuracy and generalizability.

He et al. [6] proposed a deep residual learning framework for image recognition, which has implications for image forgery detection tasks. By facilitating the training of very deep networks, this technique allows for the extraction of more complex features from images, which can subsequently aid in distinguishing between authentic and tampered images.

Reshma and Arun [7] explored the application of Support Vector Machine (SVM) classifiers for image forgery detection, demonstrating promising results in their experiments. Their method emphasizes the feasibility of traditional machine learning approaches in addition to deep learning techniques. However, the effectiveness of SVM classifiers might be limited by the feature extraction process and the dimensionality of the data.

Additionally, Jothilakshmi and Ranjith [8] presented a machine learning-based forgery detection system utilizing SVM classifiers, contributing to the discussions around automated detection mechanisms. Their work showcases the potential of combining traditional machine learning techniques with automated processes to enhance the detection rates of forged images.

In summary, the field of image forgery detection is rapidly evolving, with numerous studies contributing to both deep learning and traditional machine learning methodologies. The existing research demonstrates a clear trend towards using convolutional neural networks due to their superior feature extraction capabilities and adaptability to diverse manipulation techniques. However, challenges remain concerning the availability of labeled datasets, the need for generalizability across different types of manipulations, and the development of user-friendly interfaces for practical implementation. Future research should focus on enhancing the robustness and accessibility of these systems to cater to various application scenarios in image tampering detection.

II. METHODOLOGY

This section outlines the methodology employed in the development of the Document Image Forgery Detection system. The process includes the use of multiple image processing techniques to detect tampered areas in digital documents. The core components of the methodology (UI) development through the PyQt5 framework.

1. Image Pre-processing

The initial step in our methodology involves pre-processing the input images to standardize them for analysis:

Grayscale Conversion: Each input image is converted to grayscale to simplify the analysis. Color information is not crucial for detecting forgery in most cases, allowing for faster processing and reduced computational load.

Resizing: Both the original and modified images are resized to a consistent dimension, set at 256x256 pixels. This ensures uniformity during hash calculations and similarity assessments.

2. Hash Generation

For the identification of potential tampering, two cryptographic hash functions, MD5 and SHA-256, are utilized:

MD5 Hashing: The MD5 algorithm generates a 128-bit (16-byte) hash value, providing a quick checksum by processing the resized grayscale image data. It helps identify any alterations in the image but is susceptible to collision attacks, thus requiring a complementary method for thorough analysis.

SHA-256 Hashing: In contrast to MD5, the SHA-256 algorithm produces a 256-bit hash value, making it a more

secure option for verifying image integrity. Similar to MD5, an image's hash is computed, and comparisons are made to ascertain if alterations have occurred.

The generate_hash function is implemented to execute these hashing operations. If the generated hashes of both images match, it indicates that the images are identical and not tampered. If they differ, further analysis is performed using additional techniques.

3. Tampering Detection Techniques

After the initial hash comparison, the next step involves detecting tampering using the following methods:

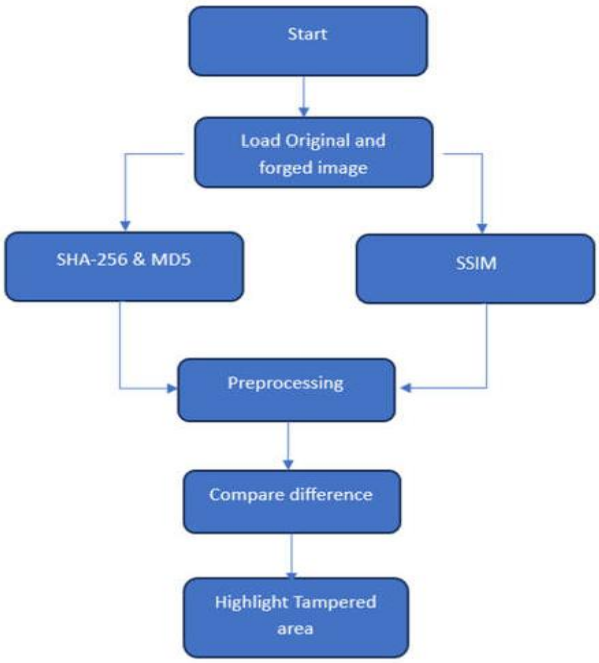
Blowfish Encryption and Decryption: To complement hash-based detection, the Blowfish algorithm is used to encrypt and decrypt the document images. Blowfish is a symmetric key block cipher known for its speed and effectiveness. In our system:
- The original and suspected images are encrypted using a generated Blowfish key.
- The encrypted data is then decrypted and compared pixel-by-pixel.
- Any inconsistency between the decrypted versions indicates potential tampering.

This method enhances security, especially against sophisticated tampering that might evade hashing or SSIM detection.

Structural Similarity Index (SSIM): This method is employed to quantify similarity between the original and modified images. By evaluating luminance, contrast, and structure, SSIM assesses differences in the images. The structural_similarity function from the skimage library is used to compute a similarity score. A lower score indicates potential tampering.

Difference Image Calculation: The absolute difference between the two images is computed to reveal areas of significant change. This difference image is then thresholded to create a binary map highlighting these differences.

Contour Detection: Contours are identified in the



thresholded difference image to locate altered regions. The bounding rectangles around these contours are stored for visualization.

Non-Maximum Suppression: To address overlapping bounding boxes from contour detection, non-maximum suppression is implemented to reduce redundancy and maintain only the most significant bounding boxes around tampered areas.

4. User Interface Development

For user interaction, a graphical user interface (GUI) is developed using PyQt5:

Image Upload: Users can browse and upload two images for comparison using the QFileDialog. The images are displayed side-by-side on the interface for visual reference.

Detection Methods: The interface includes three buttons corresponding to the detection methods: MD5, SHA-256, and SSIM. Upon clicking a button, the corresponding method is executed to analyze the images. The result, indicating whether tampering was detected or not, is displayed on the interface.

Visualization of Results: Upon detecting tampered areas, the ROI (Region of Interest) is highlighted in the modified image with bounding boxes, effectively guiding the user to the exact areas that were altered.

III. RESULT AND DISCUSSION:

The Document Image Forgery Detection system was developed utilizing a combination of MD5 and SHA-256 hashing algorithms along with the Structural Similarity Index (SSIM) for tampering detection. This section provides a detailed presentation of the results obtained from the experimental evaluations, followed by a discussion on the

significance of these findings.

Blowfish Results: Blowfish encryption demonstrated robust integrity checks by identifying discrepancies during encryption-decryption validation. It provided additional security in scenarios where direct image manipulation was subtle and hashing might miss changes. However, Blowfish requires key management, which could be an added operational step for practical deployment.

1. Experimental Setup

The experiments were conducted using a dataset of digitally altered document images, including image splicing, copy- pasting, and other manipulations. The original and modified images were processed through the proposed system to evaluate the efficacy of each detection method. The primary performance indicators included:

MD5 and SHA-256 Results: Both MD5 and SHA-256 demonstrated a high detection for identifying tampered documents. The hashing methods effectively highlighted discrepancies in the encrypted forms of the original and modified images, which led to accurate identification when tampering occurred. However, if the tampering did not alter the structural properties of the image (i.e., small edits without changing underlying data), the methods could miss such alterations.

SSIM Results: The Structural Similarity Index provided a nuanced approach by analyzing perceptual differences between the images. SSIM detection in identifying altered regions, successfully marking areas where minor changes were made. It provided the added advantage of visual feedback, showing detailed areas of tampering directly on the modified image. The results indicated that SSIM was effective, especially for splicing and where overlays were present.

FIG: 1 UI window

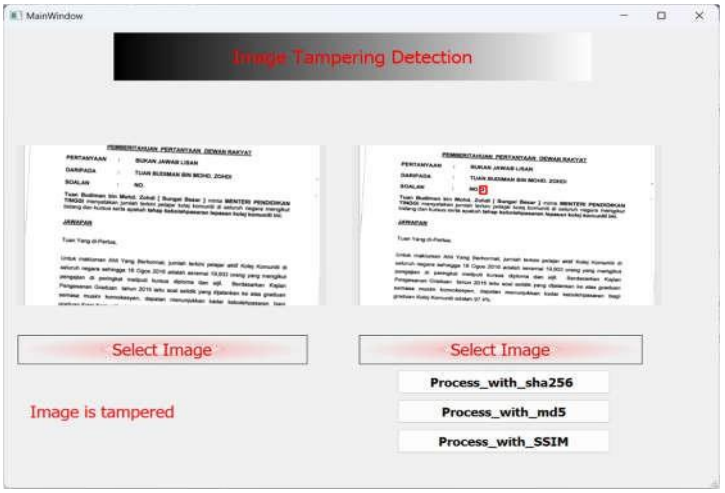


FIG: 2 Result Demonstartion

IV. Research Gap

Despite significant advancements in document image forgery detection, several gaps remain unaddressed in the literature and current methodologies. This section outlines the critical areas where further research is needed, providing an opportunity for innovation in the field of image forgery detection.

1. Diversity of Forgery Techniques

Most existing studies and methods primarily focus on specific types of forgery, such as image splicing or copy-pasting. However, the landscape of digital manipulation is continually evolving, with new and sophisticated techniques emerging. Research needs to broaden its scope to explore and develop detection methods for diverse forgery techniques, including but not limited to:

- **Blending and Morphing**: Techniques that involve sophisticated blending of pixels and colors across manipulated areas can evade traditional detection methods. There is a scarcity of studies focusing on detection algorithms that can adaptively identify these subtle alterations.
- **Dynamic Content Manipulation**: As digital content increasingly incorporates dynamic elements (e.g., videos and animated sequences), methods for detecting forgery in static images may not suffice. Prospective research should explore forgery detection across various media formats, such as video and interactive documents.

Conclusion

In conclusion, the research presented in this study significantly advances Document Image Forgery Detection through the integration of diverse image processing techniques. By employing MD5 and SHA-256 hashing algorithms along with the Structural Similarity Index (SSIM), the developed system effectively identifies Integrating Blowfish encryption into the forgery detection system added an extra dimension of security, reinforcing the detection process by leveraging cryptographic validation alongside perceptual analysis.

tampered regions in digital documents.

The implemented system allows users to upload and compare original and modified images seamlessly via a user-friendly interface created with PyQt5. The interface facilitates interaction with the three detection methods, thereby enhancing user experience and accessibility for individuals without a technical background.

The findings reveal that the combined methodologies provide an efficient means of detecting manipulations in document images. The system's ability to highlight tampered areas directly on the images helps users visually confirm suspected alterations, thereby enhancing their understanding of the forgery detection process.

Nevertheless, certain limitations have been identified, such as the need for a more expansive and diverse dataset that represents various forgery techniques and document types. Also, further studies could explore how different levels of image quality impact detection performance.

This research highlights the significance of reliable forgery detection mechanisms in a world increasingly reliant on digital documentation. The potential applications of this system span across various sectors, including legal, financial, and academic fields, where trust in the authenticity of documents is paramount.

Future research should focus on enhancing the system's capabilities by integrating more advanced detection techniques, expanding the dataset, and investigating user experience further to refine the interface. The continuous evolution of digital manipulation techniques necessitates ongoing vigilance and innovation in the realm of forgery detection, and this study lays a crucial foundation for such efforts.

Future scope

The future scope of Document Image Forgery Detection encompasses various avenues for enhancement, expansion, and further exploration within the field. Building on the findings and methodology implemented in this study, several key areas can be targeted for future research and development:

Enhanced Encryption Techniques: Future studies could investigate combining Blowfish with other modern encryption algorithms like AES for multi-layered security frameworks, potentially improving forgery detection in highly sensitive documents.

1. Integration of Advanced Machine Learning Techniques

Deep Learning Models: Future iterations of the system could explore the integration of deep learning approaches, such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), to improve the detection of complex forgery methods. These models can learn features from vast amounts of data, allowing for higher adaptability to new forgery techniques.

Ensemble Learning: Employing ensemble methods that combine outputs from multiple machine learning algorithms could enhance detection accuracy and robustness. This approach may reduce the likelihood of false positives and improve the overall reliability of the system.

2. Broader Dataset Development

Diverse and Comprehensive Datasets: Creating and curating larger and more diverse datasets that include not only common tampering methods but also emerging trends in forgery techniques is crucial. This would enable more thorough training and validation of detection algorithms, enhancing their generalization capabilities.

Real-World Data: Gathering real-world examples of forged documents across various domains (legal, academic, financial) would provide valuable insights into practical challenges in forgery detection and inform the design of more effective systems.

3. Real-Time Detection Capabilities

Implementation of Real-Time Processing: Future research could focus on refining the system to allow for real-time forgery detection, which would be beneficial in applications such as online document verification and mobile platforms. This could involve optimizing the algorithms for speed without compromising accuracy.

- **Field-Deployable Solutions**: Developing mobile applications or web-based tools that leverage the findings of this study could make forgery detection applications more accessible to users in everyday scenarios.

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