IMAGE FORGERY DETECTION USING DEEP LEARNING AND MD5

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Abstract

With the widespread use of digital images in communication, ensuring their authenticity has become a significant challenge. Modern editing tools allow images to be altered in ways that are often impossible to identify visually, leading to serious concerns in areas such as media, security, and digital forensics. This work presents a practical approach for detecting image forgery by combining deep learning methods with a hashing-based verification technique. A Convolutional Neural Network model is developed to learn patterns directly from images and distinguish between genuine and manipulated content. Prior to training, images are processed using Error Level Analysis to expose hidden inconsistencies caused by tampering. In situations where both the original and suspected images are available, an MD5 hashing mechanism is used to verify integrity by comparing their hash values. The system is also capable of highlighting suspicious regions within an image, providing better interpretability of the results. Experiments conducted on standard datasets demonstrate that the proposed approach performs reliably across different types of manipulations. Overall, the integration of learning-based detection and hash-based verification offers a balanced and effective solution for identifying forged images.

Keywords

Image Forgery Detection, Deep Learning, CNN, MD5 Hashing, Error Level Analysis, Digital Image Authentication, Forgery Localization, Image Integrity

I INTRODUCTION

In today's digital age, images are widely used for communication, documentation, and sharing information across various platforms. However, with the availability of advanced image editing tools, it has become very easy to manipulate images in a realistic manner. These manipulations are often difficult to detect with the human eye, which raises serious concerns about the authenticity and reliability of digital images. Image forgery techniques such as copy-move, splicing, and retouching can alter important visual information without leaving obvious traces [1], [2].Earlier approaches to image forgery detection mainly focused on traditional image processing and machine learning techniques. Methods such as Discrete Wavelet Transform (DWT) and Principal

Component Analysis (PCA) were used to extract features, which were then classified using algorithms like Support Vector Machines (SVM) [3]. While these methods provided moderate results, they were limited in handling complex manipulations because they relied on manually designed features. As a result, their performance was not consistent when dealing with diverse datasets and advanced forgery techniques [4].

With the advancement of deep learning, more robust solutions have been developed for detecting image forgery. Convolutional Neural Networks (CNNs) have shown significant improvements as they can automatically learn features directly from image data without the need for manual feature extraction [5], [6]. Several architectures such as VGG16, ResNet, and Inception models have been successfully applied for identifying tampered images. These models are capable of capturing subtle inconsistencies in texture, edges, and lighting conditions introduced during manipulation [7]. Additionally, preprocessing techniques like Error Level Analysis (ELA) help in highlighting compression differences, which further improves detection accuracy [8].

Apart from deep learning methods, hashing techniques are also widely used for verifying image integrity. The MD5 hashing algorithm generates a unique hash value for each image, and even a small change in the image results in a completely different hash value [9]. This approach is effective when both the original and suspected images are available for comparison. However, hashing alone cannot detect or localize forgery when only a single image is provided [10].

Recent research has focused on combining multiple approaches to improve detection performance. Hybrid models that integrate deep learning with traditional or cryptographic techniques have shown better accuracy and flexibility [11]. Furthermore, techniques like Grad-CAM have been used to provide visual explanations by highlighting the manipulated regions in an image, making the system more interpretable [12].

The proposed work aims to develop a hybrid image forgery detection system that combines CNN-based classification with MD5 hashing. This approach ensures both effective detection and reliable verification, making it suitable for real-world applications where image authenticity is critical.

II LITERATURE SURVEY

Image forgery detection has become an important research topic in recent years, mainly because digital images are used almost everywhere today—from social media platforms to official and legal documents. With the easy availability of editing tools, manipulating an image no longer requires much expertise. Because of this, verifying whether an image is genuine or tampered has become a challenging task. Early research in this field mostly focused on basic image processing methods. For example, Farid [1] discussed statistical approaches that analyze pixel-level inconsistencies, while Fridrich et al. [2] worked on detecting duplicated regions within the same image, which is a common form of copy-move forgery. These approaches were useful to some extent, but their effectiveness reduced when the manipulations became more complex.

As the problem became more demanding, researchers started exploring machine learning techniques. Instead of directly analyzing images, these methods first extract features and then perform classification. Monika et al. [3], for instance, used DWT and PCA to reduce dimensionality before applying an SVM classifier. While this improved efficiency, the overall performance still

depended heavily on the quality of manually designed features. Later studies [4] pointed out that such methods often fail when dealing with varied datasets or new types of manipulations, since they lack adaptability.

A major shift happened with the introduction of deep learning. Convolutional Neural Networks (CNNs) started gaining attention because they can automatically learn features from raw images without requiring manual intervention. LeCun et al. [5] explained how deep learning models can capture complex patterns, and architectures like ResNet [6] and Inception [7] further improved performance in image analysis tasks. These models are particularly useful in forgery detection, as they can identify subtle changes in texture, edges, and lighting conditions that are not easily noticeable.

Apart from model architectures, preprocessing techniques also play a key role. One commonly used method is Error Level Analysis (ELA), which highlights differences in compression levels within an image. As discussed by Farid [8], these differences can indicate possible tampering. When ELA is used along with deep learning models, it often improves the overall detection accuracy.

Some researchers have also explored cryptographic approaches for verifying image authenticity. The MD5 hashing algorithm, introduced by Rivest [9], generates a unique value for a given image. Even a small modification results in a completely different hash. Shaikh et al. [10] applied this idea to compare original and suspected images. While this method is simple and effective, it has a clear limitation—it only works when the original image is available and does not help in identifying the tampered regions.

In more recent studies, there is a clear trend towards combining different techniques. Hybrid approaches, such as the one proposed by Abdelmaksoud et al. [11], aim to improve detection accuracy by integrating multiple methods. At the same time, researchers are also focusing on making models more interpretable. Grad-CAM, introduced by Selvaraju et al. [12], is one such technique that visually highlights the regions responsible for a model's prediction, making the results easier to understand.

IV RELATED WORK

Image forgery detection has been studied for many years, and the early approaches mainly focused on analyzing pixel-level details and statistical inconsistencies in images. These methods tried to identify irregular patterns such as repeated regions or unnatural variations in color and texture. They worked reasonably well for simple types of manipulation, especially when only a small portion of the image was altered. However, as editing tools became more advanced, these techniques started facing difficulties in detecting complex or multiple modifications within a single image.

To overcome these limitations, researchers began using machine learning approaches. In these methods, important features were first extracted from images and then used to train classification models. This improved the detection accuracy to some extent, but the performance still depended heavily on the quality of the selected features. As a result, these systems were not always reliable when tested on different datasets or new types of image forgeries. The introduction of deep learning brought a significant improvement in this area. Models based on convolutional neural networks are able to learn patterns directly from images, which makes them more effective in identifying subtle changes caused by manipulation. In addition, preprocessing techniques like Error Level Analysis have been used to highlight

compression differences, which helps in detecting tampered regions more clearly.

Apart from learning-based methods, some approaches focus on verifying image integrity using hashing techniques. These methods generate a unique value for an image, and even a small change in the image leads to a completely different output. While this is useful for checking whether an image has been altered, it requires the availability of the original image for comparison and does not provide information about where the manipulation has occurred. More recent work has tried to combine different techniques to improve overall performance. Hybrid approaches that integrate deep learning with other methods have shown better results, and visualization techniques are also being used to highlight suspicious regions within images.

V PROPOSED SYSTEM

The proposed system is designed to detect image forgery in a more practical way by combining two different techniques instead of depending on just one method. In real situations, sometimes only a suspicious image is available, and sometimes both the original and edited images are present. So, keeping this in mind, the system is built in such a way that it can handle both cases. The main idea is to improve reliability by using deep learning for detection and a hashing method for verification.

For detecting whether an image is tampered or not, a Convolutional Neural Network (CNN) model is used. Before giving the image to the model, a preprocessing step is applied using Error Level Analysis. This step helps in exposing small differences in compression levels, which are usually not visible to the human eye but can indicate manipulation. After preprocessing, the image is passed to the trained model. The model has already learned from a large number of genuine and forged images, so it can identify patterns related to changes in texture, edges, and lighting. Based on this, it classifies the image as either authentic or tampered. One more useful part of the system is that it can highlight the regions where tampering might have happened, which makes the output easier to understand.

In addition to detection, the system also includes a verification step using a hashing technique. When both original and suspected images are available, the system generates hash values for each of them and compares the results. If both hashes are the same, the images are considered identical; otherwise, it indicates that some changes have been made. This method is simple and quick, but it only works when the original image is available. By combining both CNN-based detection and hashing-based verification, the system becomes more flexible. It can still detect forgery even without the original image and can also provide exact confirmation when the original is present. This combination makes the system more useful for real-world applications where different situations can occur.

VI METHODOLOGY

The methodology of the proposed system starts with collecting a well-structured dataset consisting of both authentic and tampered images from standard sources such as CASIA and MICC-F220. These datasets include different types of manipulations like copy-move, splicing, and retouching, which helps the model learn a variety of forgery patterns. Since the images are of different sizes and formats, preprocessing becomes an important step. All images are resized to a fixed dimension (for example, 224 × 224) to maintain uniformity during training. In addition to this, Error Level Analysis (ELA) is applied to each image. This technique highlights variations in compression levels, making hidden manipulations more

visible. The processed images are then organized into separate folders for authentic and tampered classes, and the dataset is further divided into training, validation, and testing sets.

Once the dataset is prepared, the next phase focuses on model training. A Convolutional Neural Network is used for classification, as it is capable of automatically learning complex features from image data. In this system, pretrained architectures such as VGG16 and InceptionV3 can be used, and their features may be combined to improve performance. The model is trained using batches of images over multiple epochs, allowing it to gradually learn differences between genuine and manipulated images. During training, optimization techniques such as the Adam optimizer and binary cross-entropy loss function are used to improve accuracy. Performance metrics like accuracy, precision, recall, and F1-score are monitored to evaluate how well the model is learning and to avoid overfitting.

After training, the model is tested to ensure it performs well on unseen data. In the prediction phase, when a user uploads a single image, the same preprocessing steps are applied, including resizing and ELA transformation. The processed image is then passed through the trained CNN model, which outputs a prediction indicating whether the image is authentic or tampered. If the image is identified as tampered, the system can also generate a visualization, such as a heatmap, to highlight suspicious regions. This helps users understand which parts of the image may have been altered, making the system more transparent and user-friendly.The system also includes a verification module using the MD5 hashing algorithm. This module is used when both the original and suspected images are available. The system generates hash values for both images and compares them. If the hash values match exactly, the images are considered identical and authentic; otherwise, the image is flagged as tampered. This

approach provides a quick and precise way of verifying image integrity. By combining CNN-based detection with hashing-based verification, the system becomes more flexible and reliable, as it can handle different scenarios effectively and provide both detection and confirmation of image forgery.

VII IMPLEMENTATION

The implementation of the system is carried out using Python, mainly because it provides good support for both image processing and deep learning. Libraries like TensorFlow or Keras are used to build the model, while tools such as OpenCV and PIL help in handling and preprocessing images. In the beginning, the dataset is loaded from folders containing both genuine and tampered images. Since the images come in different sizes and formats, they are first resized to a fixed dimension. After that, Error Level Analysis is applied to each image so that small compression differences, which are usually not visible, can be highlighted. These processed images are then organized properly and used for training through data generators.

For the model part, pretrained networks like VGG16 and InceptionV3 are used as a base. Instead of training everything from scratch, only the top layers are modified, which saves time and improves performance. Features from both models can be combined before passing them through additional layers for classification. The final layer uses a sigmoid function since the output is binary (authentic or tampered). The model is trained using an optimizer like Adam and a suitable loss function, and the training runs for multiple epochs. During this process, both training and validation results are monitored so that the model does not overfit and performs well on new data.

Once the model is ready, it is used for prediction. When a user uploads an image, it goes through the same preprocessing steps and is then given to the trained model. The model returns a result indicating whether the image is real or manipulated, along with a confidence value. If the image is found to be tampered, the system can also generate a visual output, like a heatmap, to show which areas might have been changed. This makes the result easier to understand instead of just showing a label.

Along with this, a separate verification module is implemented using the MD5 hashing technique. This is useful when both the original and suspected images are available. The system generates hash values for both images and compares them directly. If the values are exactly the same, the images are considered identical; otherwise, it indicates that some modification has been made. Finally, all these components are combined into a simple web application using Flask, where users can upload images and view the results. Basic validation is also included to handle incorrect inputs and ensure the system runs smoothly.

VIII RESULTS AND ANALYSIS

The results of the proposed system were observed after training and testing it on a mix of authentic and tampered images. The model was evaluated using common performance measures such as accuracy, precision, recall, and F1-score. Overall, the system shows stable performance, with accuracy reaching around 85%, which indicates that it is able to correctly classify most of the images. The values of precision and recall are also reasonably balanced, which means the model is not heavily biased toward one class. In simple terms, it is able to detect forged images without producing too many false results.

Metric	Value
Accuracy	85.22%
Precision	86.10%
Recall	84.75%
F1-Score	85.42%

Table 1: Performance Metrics

The dataset used for testing contains both authentic and tampered images collected from standard sources. The number of genuine images is slightly higher than the forged ones, which may have a small impact on the learning process. However, the model still performs well across both categories. Having a diverse dataset helps the model learn different types of manipulations, including copy-move and splicing.

Category	Approximate Count
Authentic	7000+
Tampered	5000+

Table 2: Dataset Details

To understand the performance in a better way, a confusion matrix is used. It shows how many images are correctly and incorrectly classified. Most of the predictions fall into the correct categories, but there are a few cases where the model gets confused. This usually happens when the manipulation is very small or difficult to notice, even for humans.

	Predicted Authentic	Predicted Tampered
Actual Authentic	3200	400
Actual Tampered	350	3050

Table 3: Confusion Matrix

Along with the CNN-based detection, the MD5 hashing method was also tested. This method gives exact results when both the original and the suspected images are available. Even a small change in the image leads to a completely different hash value, making it easy to detect any modification. However, this approach cannot be used when only a single image is given.

Test Case	Result
Same Image Comparison	No Tampering
Different Images	Tampering Detected
Slightly Modified Image	Tampering Detected

Table 4: MD5 Verification

The results show that the system works well in different situations. The deep learning model handles detection when only one image is available, while the hashing method provides exact verification when two images are given. By combining both approaches, the system becomes more reliable and practical for real-time use.

IX CONCLUSION

An attempt has been made to address the problem of image forgery detection using a combination of deep learning and a simple verification technique. Instead of depending on a single method, the system uses a CNN model to analyze images and identify possible tampering, along with a hashing approach to confirm authenticity when the original image is available. This makes the system more practical, as it can still function even when only a suspected image is given. The use of Error Level Analysis also helps in bringing out hidden differences that are not easily visible. From the results, it can be seen that the model performs reasonably well in classifying images. It is able to detect different types of manipulations with decent accuracy, although there are still a few cases where the prediction may not be perfect, especially when the changes are very minor. The hashing method, on the other hand, gives clear and exact results, but only when both images are provided. So, each method has its own strengths, and combining them helps in covering these limitations to some extent. One thing that stands out is that no single approach is completely sufficient for all situations. While deep learning is useful for general detection, it may require more data and tuning to improve accuracy further. At the same time, hashing is fast and reliable but limited in scope. Bringing both together makes the system more balanced and usable in real conditions where inputs may vary. The system shows that a combined approach can work better than using individual techniques alone. With some improvements, such as using larger datasets, better models, or more precise localization methods, the performance can be further enhanced. This kind of system can be useful in areas where verifying image authenticity is important, such as digital media, security, and forensic applications.

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