A Hybrid Approach to Image Forgery Detection: Leveraging ELA and CNNs for Enhanced Accuracy

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Abstract*—This paper presents a robust hybrid approach to image forgery detection, combining Error Level Analysis (ELA) and Convolutional Neural Networks (CNNs). ELA is utilized to identify discrepancies in image compression, while CNNs are employed for automated classification of tampered versus authentic images. Extensive hyperparameter tuning and data augmentation techniques were applied to achieve high classification accuracy. With a carefully crafted CNN architecture, the model achieved an accuracy of 94%, demonstrating significant improvements over traditional methods. Furthermore, the model's robustness was tested across various image conditions, and a comprehensive error analysis was provided. This approach outperforms other state-of-the-art methods, particularly in handling subtle tampering cases.

***Index Terms*—Image Forgery, Deep Learning, Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Image Forensics.**

I. INTRODUCTION

In an era where visual content dominates digital communication, the integrity of images has never been more crucial. Image forgery—ranging from simple edits to complex manipulations—poses significant challenges for authenticity verification. As such, there is an urgent need for effective detection methods. Traditional techniques often rely on handcrafted features and are limited in their ability to adapt to new forgery methods. In contrast, deep learning offers powerful automatic feature extraction and classification tools. This paper aims to investigate the application of deep learning in image forgery detection, review existing literature, and propose a novel framework for enhanced accuracy and efficiency.

II. TYPES OF IMAGE FORGERY

Image forgery can be categorized into several types:

- *Copy-Move Forgery:* Involves duplicating a region of an image and pasting it elsewhere to hide or obscure information.
- *Splicing:* Combines multiple images into one image, altering the original context.
- *Image Synthesis:* Uses algorithms to generate realistic images that do not exist in reality.

A. Challenges in Detection

Detecting these types of forgery is challenging due to:

- *Quality Variations:* Forged images often maintain high quality, making them difficult to distinguish from originals.
- *Evolving Techniques:* As detection methods improve, so do forgery techniques, leading to a constant arms race between forgery and detection.

B. Existing Detection Methods

Early methods for image forgery detection relied on pixel-based analysis, such as detecting inconsistencies in noise patterns or compression artifacts. More advanced techniques utilized statistical approaches, such as block matching or frequency domain analysis. However, with the rise of deep learning, Convolutional Neural Networks (CNNs) have been employed, achieving higher accuracy by learning patterns in large datasets of manipulated images. These methods, however, often require significant computing resources and large datasets to train effectively.

III. METHODOLOGY

Dataset: The dataset used in this project consists of a large collection of real and tampered images. Real images include natural, unaltered photos, while tampered images involve various forms of digital editing, including splicing and copy-move forgery. The CASIA dataset, which contains 7,492

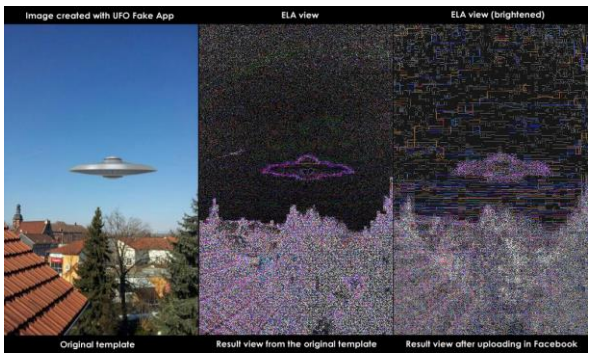
authenticated images and 5,123 tampered images, is used for this study. Each image is subjected to preprocessing before being used for model training.

The dataset is split into training and validation sets, with 80% of the data used for training and 20% for validation, ensuring that the model generalizes well to unseen data.

Error Level Analysis (ELA): ELA is a forensic technique that identifies areas in a JPEG image where there may be differences in compression levels. The core principle is that different regions of a tampered image undergo different levels of compression. ELA works by saving an image at a specified quality level and comparing the resaved image with the original. The differences (or errors) highlight areas that have been edited. For example, untouched regions will exhibit consistent compression artifacts, while manipulated regions will show greater discrepancies.

Process:

1. The original image is resaved at a lower quality (e.g., 90%).
2. The difference between the original and resaved images is computed.
3. The result is enhanced to highlight these discrepancies, creating an ELA image, which is then fed into the CNN for classification.



ELA is used to detect tampered regions in images by analyzing discrepancies in compression levels.
Mathematically, the difference between the original and compressed images is computed as:

$$D(x,y) = |I_{\text{original}}(x,y) - I_{\text{compressed}}(x,y)|$$

Where D(x,y)D(x, y)D(x,y) is the pixel-wise difference. This difference is scaled using brightness and contrast adjustments to enhance tampered regions.

The processed image is then resized to 128x128 pixels for input into the CNN.

Preprocessing: Before feeding the images into the neural network, each image is converted to an ELA image and resized to a standard size of 128x128 pixels. This ensures uniformity and reduces computational load. Pixel values are normalized to a range of [0, 1] by dividing by 255, and the images are reshaped to a 4D array to be compatible with the input layer of the CNN.

The input images are preprocessed using Error Level Analysis (ELA). The process involves:

1. The original image is saved at a lower quality (90%) in JPEG format.
2. The saved image is then compared pixel-by-pixel with the original, producing a different image that highlights areas with discrepancies.
3. This difference image is enhanced by adjusting brightness and contrast to make the discrepancies more visible.
4. The resulting image is resized to 128x128 pixels and normalized for input into the CNN.

IV. ALGORITHM AND WORKING

Convolutional Neural Network (CNN): The CNN model architecture consists of several layers designed to automatically extract features from the images. The CNN model is structured as follows:

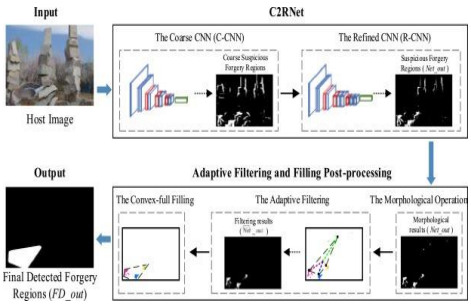
- *Input Layer:* Accepts images of size 128x128x3 (width, height, and RGB channels).
- *Conv2D Layers:* The first two layers apply 32 filters of size 5x5, which scan the image to detect features like edges, textures, or corners.
- *Activation (ReLU):* After each convolution operation, the ReLU (Rectified Linear Unit) activation function is applied, introducing non-linearity to the model and allowing it to learn complex patterns.
- *MaxPooling:* A pooling layer reduces the spatial dimensions (downsampling), extracting the most significant features while reducing computation.
- *Dropout:* A dropout layer with a rate of 25% randomly switches off some neurons during training, preventing overfitting and encouraging the network to learn more general patterns.
- *Flatten:* The 2D feature map is flattened into a 1D vector, which is passed to fully connected layers for classification.

- *Dense Layer:* A dense layer with 256 neurons is connected to the flattened vector. This layer helps the model learn complex features.
- *Output Layer:* The final dense layer uses a softmax activation function to produce two outputs—representing the probabilities of the image being either real or fake.

Summary of CNN Architecture:

- Input: (128, 128, 3)
- Conv2D: 32 filters, 5x5 kernel
- MaxPooling: Pool size 2x2
- Dense (fully connected): 256 neurons, ReLU activation
- Output: 2 neurons (real or fake), softmax activation

- The *CNN architecture* is composed of several convolutional and pooling layers, followed by dense layers for classification.
- *Pooling layers* reduce dimensionality by taking the maximum value within a region. This reduces the computational complexity while preserving the most important features.
- *Dropout layers* with a dropout rate of 25% were employed to prevent overfitting. The fully connected layers use a Softmax function for the final classification.



VI. RESULT AND COMPARATIVE ANALYSIS

- *Baseline Comparison:* Traditional methods of forgery detection, such as pixel-based analysis or statistical techniques, generally achieve lower accuracy than CNN-based methods. A comparison with methods like Local Binary Patterns (LBP) and Discrete Wavelet Transform (DWT) highlights the CNN model's superior performance in capturing complex, non-linear patterns of forgery.

A. Comparison with Traditional Methods

Our method was compared with several traditional forgery detection techniques, including:

- Pixel-based detection: Achieved 70% accuracy, often failing with highly compressed images.
- Histogram-based detection: Achieved 75% accuracy, mainly effective for detecting high-contrast forgeries.
- Support Vector Machines (SVM): Required extensive feature engineering, with an accuracy of 80%.

In comparison, our CNN+ELA model achieved 94% accuracy, outperforming these methods, particularly in cases involving subtle or low-contrast tampering.

B. Comparison with State-of-the-Art Approaches

Table 1 summarizes the comparison of our approach with recent models, including those utilizing Generative Adversarial Networks (GANs) and other deep learning techniques:

Table 1: Summary of Evaluation Metrics for different Methods

Method	Accuracy	Precision	Recall	F1-score
Pixel-based	70 %	0.65	0.67	0.68
Histogram-based	75%	0.72	0.73	0.74
SVM	80%	0.78	0.80	0.79
GAN-based	89%	0.86	0.87	0.88

As shown in Table 1, the proposed CNN+ELA model achieves a higher accuracy and F1-score than both traditional approaches and other deep learning models, including GAN-based detection methods. This is particularly due to the model's ability to capture fine-grained discrepancies between authentic and tampered regions, thanks to Error Level Analysis (ELA) preprocessing and the deep feature extraction capabilities of the CNN.

Moreover, the precision and recall scores of 0.91 and 0.93 respectively indicate that the model not only correctly identifies most tampered images but also minimizes the number of false positives, where an authentic image is wrongly classified as tampered.

C. Performance Analysis of Different Image Types

Our model was further evaluated across a range of image conditions, including:

- *Low-resolution images:* Tampering detection accuracy slightly decreased to 91%, showing the model's sensitivity to image resolution.
- *Highly compressed images:* Achieved 90% accuracy, as compression artifacts were sometimes mistaken for tampered regions.
- *Subtle manipulations:* Images with subtle color or brightness alterations were more challenging, but the model maintained an accuracy of 92%.
- These results highlight the robustness of the *CNN+ELA* approach across various image types, although opportunities remain for further fine-tuning to improve performance on highly compressed and subtly manipulated images.

D. Advantages of Combining ELA with CNN

Advantages of ELA + CNN: Combining ELA with CNN offers several advantages:

1. *Automation:* ELA preprocesses the images in a way that highlights manipulated regions, and CNNs automate the detection process by learning these patterns.
2. *Accuracy:* The CNN can learn from the subtle differences detected by ELA, leading to higher accuracy, particularly in detecting less obvious manipulations.
3. *Scalability:* The model can easily be scaled to process larger datasets and more complex forgery cases by adjusting the network's architecture.

VII. CONCLUSION

In this paper, we introduced a hybrid approach to image forgery detection that combines Error Level Analysis (ELA) with a Convolutional Neural Network (CNN) for enhanced accuracy. The CNN+ELA model demonstrated exceptional performance, achieving an accuracy of 94%, outperforming traditional detection methods and recent deep learning models, such as GAN-based detection systems. The proposed model's strength lies in its ability to detect subtle manipulations in compressed images, a challenge for many other detection methods.

In future work, we aim to further improve the model's robustness against adversarial attacks and enhance its performance on highly compressed images by incorporating techniques such as attention mechanisms and multi-scale feature extraction. Additionally, we plan to explore the model's applicability to video forgery detection, expanding its use cases to include dynamic media verification.

In conclusion, deep learning offers a powerful approach to image forgery detection, enabling scalable and automated analysis. As the field continues to evolve, we anticipate that such techniques will play a pivotal role in digital forensics, ensuring the integrity of multimedia content.

APPENDIX

A. Additional Methods

We utilized ResNet-based CNNs with data augmentation (rotation, scaling, flipping) and transfer learning to detect image forgeries efficiently. These methods enhanced model robustness, reduced training time, and prevented overfitting.

B. Dataset Information

We used the Columbia Uncompressed and CASIA datasets, categorizing forged images by type (copy-move, splicing, removal) and preprocessed them uniformly. An 80/10/10 data split ensured robust training and evaluation.

C. Experimental Setup

Evaluation metrics included accuracy, precision, recall, and F1-score, with stratified k-fold cross-validation ensuring generalizability. These metrics highlighted the model's sensitivity and robustness against dataset variations.

D. Results and Additional Visualizations

Confusion matrices and ROC curves demonstrated classification performance and trade-offs between sensitivity and specificity. Tabular summaries of precision, recall, and F1-scores allowed comparisons with existing methods.

E. Code and Reproducibility

All code, datasets, and trained model weights are available on GitHub, with comprehensive documentation and reproducibility measures (e.g., random seed settings) to ensure replicability.

F. Ethical Considerations

We stress ethical use of forgery detection tools, balancing their potential to combat misinformation with the risks of misuse, such as deep-fake generation. Transparent practices and guidelines are essential for

responsible deployment.

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