Region-Wise Image Forgery Localization Using CNNs and Error Level Analysis

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Abstract. In today's digital era, ensuring image authenticity is crucial for maintaining trust and integrity. This study presents a CNN-based approach for image forgery localization, integrating Error Level Analysis (ELA). Using the CASIA v2.0 dataset, our model achieved an F1-score of 0.5712 and an AUC-score of 0.7678, showing its effectiveness. Performance analysis across different tampering percentages shows improved accuracy for higher tampering levels, reaching an F1-score of 0.8099 for 20-40% tampering, 0.8331 for 40-60%, 0.8331 for 60-80%, and 0.8217 for 80-100% tampering. Particularly, for images with more than 20% tampering, our model consistently achieves an F1-score above 0.80, making it highly reliable for significant manipulations. Unlike complex architectures such as Mantra-Net (F1-score: 0.566, AUC: 0.817) and ObjectFormer (F1-score: 0.579, AUC: 0.758) that require extensive computational resources, our approach is lightweight and computationally efficient, making it suitable for real-world applications where high-performance hardware may not be available. These results validate the robustness of our method in accurately localizing tampered regions with high reliability and efficiency.

Keywords: Error Level Analysis, Image Forgery, CNN, Image Tampering Detection, Region Level Localization.

1 Introduction

In today's digital age, image forgeries have become increasingly accessible, posing serious threats to the authenticity and correctness of online content, such as pictures and videos, especially in domains like media, forensics, and security. Though Detection of forgery in images is very crucial even accurately localizing the tampered images is important to know about the extent of tampering. Despite significant advancements, accurately pinpointing manipulated areas in images remains a challenge. Forged regions often blend seamlessly with genuine content, making it difficult for many existing methods to detect subtle signs of tampering. This highlights the need for an innovative architecture that can adapt and learn to identify the fine details that distinguish forgeries from authentic regions.

In this paper, we propose a novel architecture for image forgery detection focusing on the accurate localization of tampered regions by predicting binary masks for tampered images. Our approach ensures accurate detection and reliable performance evaluation by comparing these predictions with ground truth binary masks.

The remainder of this paper is organized as follows: Section 2 reviews related works in image forgery detection and localization. Section 3 details the proposed architecture and methodology. Section 4 presents experimental results and comparisons. Finally, Section 5 concludes the paper with future directions.

2 Related Works

Research in image forgery detection and localization has significantly evolved over the years, driven by the growing complexities introduced by AI tools and increasing demand for detection methods. The initial approaches mostly focused on detecting whether an image is tampered or not [8,14,16] with, followed by localization of tampered regions by identifying pixel-level inconsistencies and anomalies. However, with advancements in Machine Learning and Deep Learning, It is observed that the field has undergone significant evolution in research, discussed in Table 1. This survey section provides an overview of these state-of-the-art techniques, analyzing their strengths, limitations, commonly used datasets, and evaluation metrics to offer a clear understanding of the current standards in the field.

Table 1: Comparative Analysis of Image Forgery Detection Models

Model Used	**Advantages**	**Research Gaps**	**Performance Metrics**
Modified UNET (BN+Identity Blocks) [9]	Successfully localized medical, natural, identity images.	Failed localizing scanned documents.	Scanned-Documents-89%, Other images-99%
Block Match Copy-Detection Forgery Algorithm [6]	Successfully localizes tampered regions in Copy-Move images.	May lead to false positives in uniform areas like the sky.	Accuracy-97.7, FPR-0.5112

Model Used	Advantages	Research Gaps	Performance Metrics
Graph Convolutional Networks + SVM Classifier [21]	Captures complex spatial and structural relationships, enhancing feature representation.	Lacks comparisons with recent state-of-the-art models; only addresses copy-move forgeries.	Accuracy and F1-score exceeded 99% after 25 epochs.
ResNet18 + PSO + GRU [10]	Performs better than SVM and other latest models.	Localization can be implemented further.	Accuracy-96.25%
D-Net (Dual-Encoder Network) [26]	Enhances pixel-level precision, robust to noise, JPEG compression, and resizing.	Focuses solely on splicing forgeries; struggles with same-image forgeries.	CASIA: Precision=0.866, Recall=0.852, F1 Score=0.859
ELA + VGG16 and UNET [3]	Outperforms several existing methods.	Could utilize a lightweight architecture.	Accuracy – 91.7, Precision-93.5, IoU Score-0.80, F1-score – 0.777
Two-Branch Transformer + AHFM [13]	Effective feature fusion improves localization performance.	Heavily relies on RGB and noise domains, which may not complement each other.	CASIA: F1=0.749, IoU=0.73, AUC=0.897
Noiseprint-based Forgery Localization + Siamese CNN [5]	Outperforms traditional PRNU-based methods.	Reduced performance with geometrically misaligned reference images or raw formats.	AUC Score-0.967, F1 Score-0.724
DMFF-Net [25]	More accurate and robust than traditional methods.	Feature fusion modules can further improve performance.	AUC - 99.6%
Reliable Fusion Map (RFM) [27]	Improves localization using patch texture, CNN confidence, and density distribution.	High computational cost and lower performance in low-texture regions.	Accuracy-94.9%

Model Used	Advantages	Research Gaps	Performance Metrics
GFIL (Generalizable Forgery Image Localization) [28]	Performs well on unseen and seen forgeries, excels in detecting fusion edits.	Slight performance drop in detecting seen forgeries compared to specialized methods.	Unseen: F1-score - 0.6703, IoU – 0.321 Seen: F1-score – 0.7815, IoU – 0.5037
CNN-Based Camera Feature Extraction + Clustering [1]	Outperforms state-of-the-art traditional methods for spliced images from different cameras.	Relies on camera model artifacts, limiting generalization.	Accuracy: 91% on known models, 81% on unknown models, Localization: 90% (known), 82% (unknown)
Dual-Domain CNN (D-CNNs) [20]	Outperforms traditional methods in tampered region localization.	Heavy reliance on dataset-specific post-processing limits generalization.	F1 Score-0.59

2.1 State-of-the-Art Models

Let us start with state-of-the-art models, in [24] researchers proposed a groundbreaking paper named Mantra-Net, which gave outstanding results without any pre- or post-processing s, mainly focusing on both detection and localization. Mantra-Net is a fully convolutional network that utilizes a VGG-based feature extractor that is used to identify various forgery traces and an LSTM-based detection module that is used to pinpoint forged regions. This model achieved an AUC score of 81.7% pixel level, an F1 score of 0.566 on the CASIA data set. However, these metrics are outperformed by the [17] with the AUC score of 86.3%. The model they proposed uses ResNet-50 as an encoder for two streams. One stream takes the input as an RGB image, while the other takes Spatial Rich Model (SRM) filters, which are used to enhance the high-frequency information of the image. Later, the features are fused channel-wise, and these fused features are sent to the Atrous Spatial Pyramid Pooling (ASPP), which is used to capture multi-scale contextual information by applying atrous (dilated) convolutions at different rates module for getting multi-scale information later passed through contrastive learning technique(which separates tampered and authentic regions). This approach is well known for outperforming [24].

2.2 Error Level Analysis Based Techniques

Error level analysis(ELA) is a powerful method used by many models in their study. Such as in [15] researchers used a combination of ELA and CNN model for the detection of image splicing by ELA which uses variations in compression levels that indicate tampering. Initially, the image is converted into a lossy format. Later, the error level is calculated by subtracting the previous image. This error image is then applied to rescaling and high-pass filtering, which are used to intensify pixel-level errors. This error level image is fed into the CNN with 2 conv layers,1 max pooling, dropout is used. This approach performed well on the CASIA data set with 94.1% test accuracy and 99.05% train accuracy.

Another study in [4] uses a combination of ELA with a customized VGG16 model, where ELA-transformed images were resized, normalized, and passed through a network with initial frozen layers, batch normalization, and drop out. This framework utilized transfer learning which helped them to a high f1 score of 0.90 on CASIA v2.0 [18] and accuracy of 90% but the paper leaves scope for localization as they focused more on classification.

ELA has been a successful and most used technique in this field notably the in Copy move forgery type proved in [23] a DL-based CAE model was proposed with an accuracy of 99.2% on MICC-F220 data set. Initially, images undergo image augmentation steps, later the images are added with the respective ELA. The CAE architecture includes convolutional and deconvolutional layers for encoding and reconstructing features. A Similar CNN methodology with some changes is proposed in [2], which uses Noise maps using SRM, additionally with the ELA image with 30 high pass filters. These two inputs are sent into the dual branch CNN architecture with ELA image to the first branch and noise residuals to the second branch. Hyperparameters such as RMSprop are used to bring down the loss of the model. This approach got an accuracy of 98.55% accuracy and an f1 score of 0.98 on the CASIA data set, Localization isn't done in this paper which leaves room for the future and this can be directly related to our methodology where we are utilizing similar methodology.

Other than ELA some researchers solely used CNN combined with Machine Learning models and Ensemble models [11] for detection and localization, such as in [22] a methodology was proposed using the CNN-SVM approach. This paper utilizes CNN for extracting complex features and patterns and features are sent to the SVM classifier which classifies the regions as authentic or tampered. However, the other steps used are a standout point in this method such as in preprocessing, various images with augmented styles were sent and later the image was divided into patches and sent to the CNN. This model has an accuracy of 92.6% and an AUC of 92.69%. A Similar methodology was used in [16] which used a recursive block-based key-point matching algorithm for copy-move forgery. The paper only focuses on tampering detection rather than localization.

Similarly modified CNN was used in [12] which proposes a Multi-Scale Convolutional Neural Network (MSCNN) framework to identify and localize tampered regions, using a sliding window at different scales to identify fine-grained and broad image features. The CNN architecture includes SRM filters, multiple convolutional layers, and a fully connected layer for tampering probability estimation. The methodology is validated on datasets such as the IFS-TC and Realistic Tampering Data set (RTD) got an F1-Score of 0.4063.

After all, all these methods proposed their approaches, Each method has its benefits and limitations, excelling under specific conditions. While models like ManTra-Net and CFL-Net set benchmarks for detection and localization, ELA-based methods remain widely used due to their simplicity and effectiveness in preprocessing. Building on the insights from these papers, we propose a new methodology using ELA-CNN, outlined in Section 3, which builds on these advancements to address existing gaps in forgery detection and localization.

3 Methodology

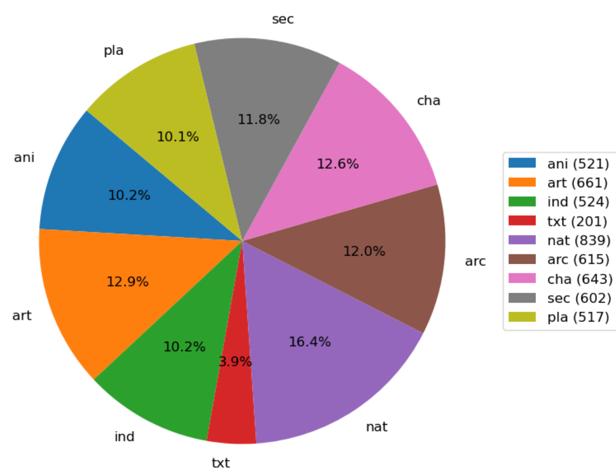


Fig. 1: Distribution of category

3.1 Dataset Description

The dataset utilized in this study is CASIA v2.0 [18] which consists of 7,200 images in the authentic set and 5123 tampered images in the tampered set [7], along with ground truth binary masks. The dataset comprises 35.68% image splicing tampering and 64.32% copy-move tampering. The average tampering percentage in the dataset is 8.96%. The range of tampering percentage varies from 0.02% to 96.30%. The dataset contains various categories which include architecture (arc), art, characters (cha), indoor scenes (ind), nature (nat), plants (pla), animal(ani), and textures (txt). The Distribution of each category is shown in Fig. 1.

3.2 Model Architecture

We utilized the original tampered image (X1) and the ELA image (X2) generated from Algorithm 1, as both contribute significantly to the model's ability to detect and localize tampered regions more effectively. X1 provides a visual representation from which critical and useful features can be learned and X2 highlights signs of editing such as differences in compression levels. The learnings from these images help the model to train better making it easier to localize the forgery. The Tampered image, and ELA image are shown in Fig. 3.

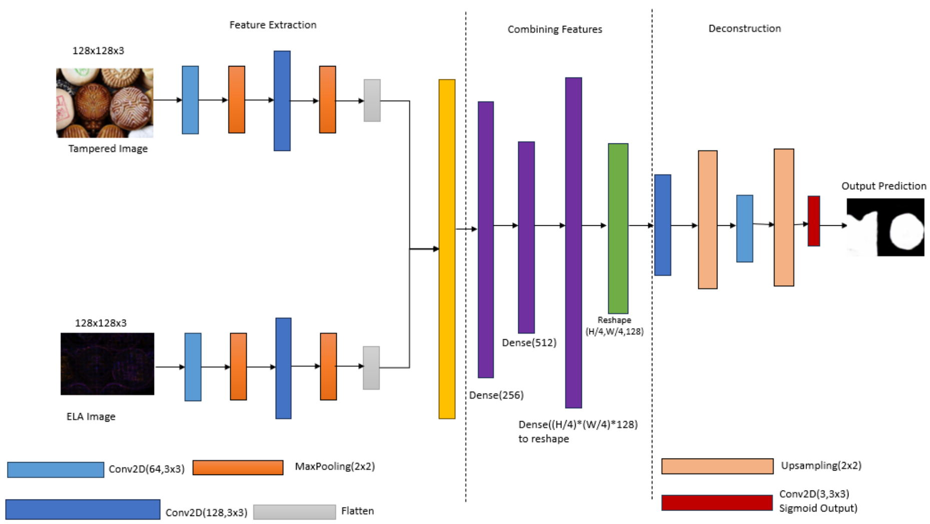
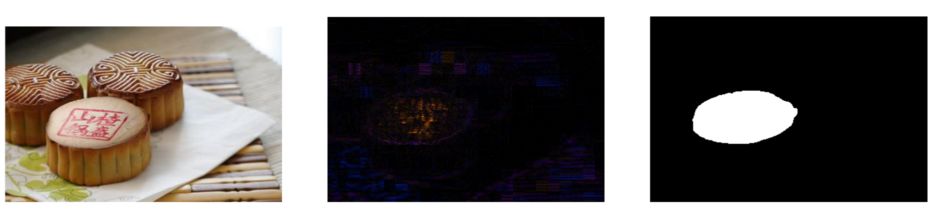


Fig. 2: Architecture of the proposed model. The original image and ELA image are processed through convolutional and pooling layers, concatenated, and passed through dense layers for feature learning, followed by image reconstruction.



(a) Tampered Image (X1) (b) ELA Image (X2) (c) Ground Truth

Fig. 3: Visualization of input images for forgery detection.

The original image and the ELA image each go through two convolutional layers and two max-pooling layers (The model architecture is visually represented in Fig. 2).

Algorithm 1 Error Level Analysis (ELA) Image Generation

1. **Load the Image:**
   Load the tampered image Img_Tp from the dataset.
2. **Re-save the Image:**
   Save the Img_Tp with slightly reduced JPEG quality (e.g., 98%) to introduce compression artifacts.
   Denote the re-saved image as Img_ELA.
3. **Calculate Pixel-wise Difference:**
   For each pixel (x, y) in Img_Tp and Img_ELA, compute the difference:
   $$Diff(x, y) = |Img\_Tp(x, y) - Img\_ELA(x, y)|$$
4. **Calculate Maximum Difference:**
   Compute the maximum value of the difference:
   $$Max(Diff) = \max_{(x,y)} |Img\_Tp(x, y) - Img\_ELA(x, y)|$$
5. **Scale the Difference:**
   Calculate the scale factor as:
   $$scale\_factor = \frac{255}{Max(Diff)}$$
   Then, for each pixel (x, y) in $Diff$, scale the difference:
   $$Img\_ELA\_Sc(x, y) = scale\_factor \cdot Diff(x, y)$$
6. **Output the ELA Image:**
   The resulting image Img_ELA_Sc highlights potential tampered regions with brighter areas indicating significant discrepancies.

The `Conv2D` layers help identify features and patterns like edges, textures, and tampering artifacts.The max-pooling layers make computations more efficient by retaining important information while reducing the size of the feature maps.

The features extracted from both inputs are then concatenated into a single vector. This representation is then passed through a series of dense layers, as shown in the architecture, where it learns a meaningful encoding of tampered and non-tampered features.

The refined features obtained from the dense layers are reshaped into a 3D tensor, which is useful for the image reconstruction process. This tensor is passed through a series of convolutional layers and up-sampling layers. The convolutional layers add fine details to the image, helping it appear more accurate and natural, while the up-sampling layers increase the spatial dimensions to match those of the original image. Finally, the output layer applies convolution with

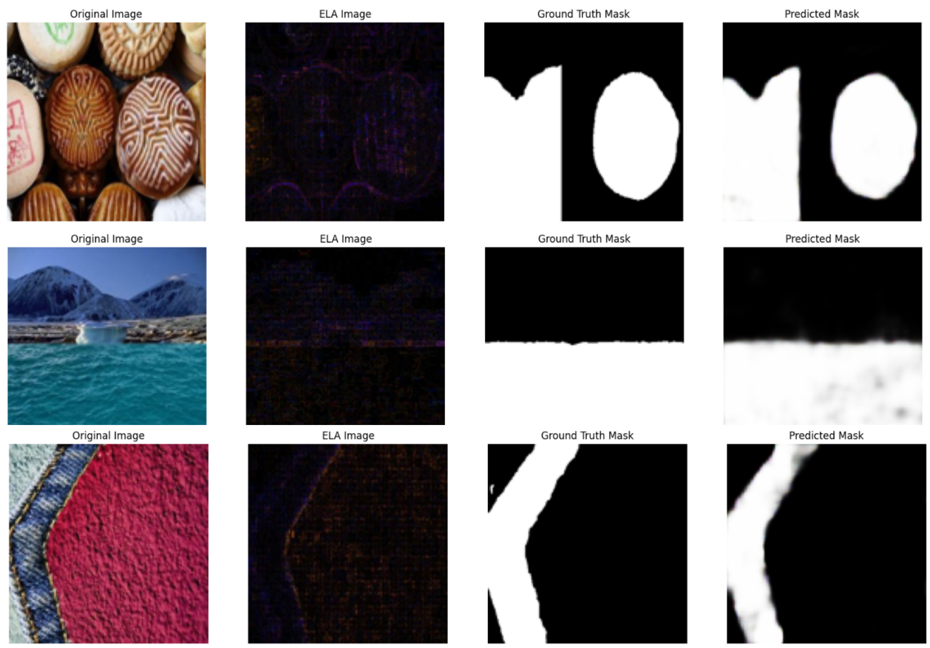


Fig. 4: Predictions of the model on the test dataset.

three filters, providing outputs for each color channel. Sigmoid activations normalize the values between 0 and 1, producing a clean and reconstructed mask without distortions. The predicted masks and the ground truth masks are visualized in Fig. 4.

3.3 Error Level Analysis

Error Level Analysis (ELA) is used to detect areas of an image that have been edited or manipulated by highlighting differences in compression levels. Compressive variation is identified by considering why different parts of an image compress differently; this happens especially in pictorial images where certain portions have been edited. This is because when saving images in compressed formats, the compression algorithm reduces the size of the file through a simplification of the given patterns, colors, or textures. Edited regions commonly compress differently because they would have undergone separate processing, or perhaps added afterwards. Error Level Analysis (ELA) detects these differences as it saves the image using a known compression level and then compares it to the actual image. Generally, those regions that have not undergone any changes will consistently possess compression artifacts, whereas a changed region will present its inconsistency or difference.

Among various feature extraction methods, Error Level Analysis (ELA) was chosen due to its ability to highlight compression inconsistencies which is clearly investigated in [19], making it particularly effective for detecting image manipulations. Unlike Spatial Rich Model (SRM), which focuses on statistical noise patterns, or Noiseprint, which relies on camera sensor artifacts, ELA directly exposes tampered regions by analyzing recompression artifacts. Additionally, DCT-based approaches operate in the frequency domain and may require additional pre-processing steps, making them computationally expensive. ELA, on the other hand, is straightforward to implement and computationally efficient, making it ideal for real-time or resource-constrained environments. By leveraging ELA alongside CNNs, our model effectively localizes forgeries without requiring extensive preprocessing or handcrafted features.

4 Experimental Results

4.1 Why F1-Score is a good metric?

As most pixels in the ground truth mask are black, a model that predicts everything as black will still achieve a higher accuracy. However, the accuracy metric can be misleading. The F1-score, on the other hand, focuses on the positive class (black in our case) and balances precision and recall:

- **Precision** measures the model's ability to accurately predict non-tampered regions (black pixels, labeled as 0), minimizing false positives.
- **Recall** evaluates the model's effectiveness in identifying tampered regions (white pixels, labeled as 1), minimizing false negatives.

Non-tampered regions (black pixels) typically dominate the mask, so predicting only black may result in a higher precision score but the recall will be low, as tampered regions (white pixels) are incorrectly predicted as non-tampered (False Negatives), which lowers the F1-score. Thus, the F1-score serves as a

Table 2: Confusion Matrices for Train and Test Data

	Train Data		**Test Data**	
	F (Pred)	**R (Pred)**	**F (Pred)**	**R (Pred)**
F (Act)	49,428,117	616,338	11,556,637	689,399
R (Act)	1,625,380	7,312,565	1,224,817	1,274,747

Note: F: Fake, R: Real, Pred: predicted values, Act: actual values

better metric when comparing the binary mask and the predicted mask. The model's performance metrics, including F1-score, Precision, Recall, and AUC, for both the training and test sets are presented in Table 3. Additionally, the confusion matrices for the training and test sets are shown in Table 2.

Table 3: Precision, Recall, F1-score, and AUC Score for Training and Testing

Metric	**Training**	**Testing**
Recall	0.8181	0.5100
Precision	0.9223	0.6490
AUC Score	0.7578	0.7678
F1-score	0.8671	0.5712

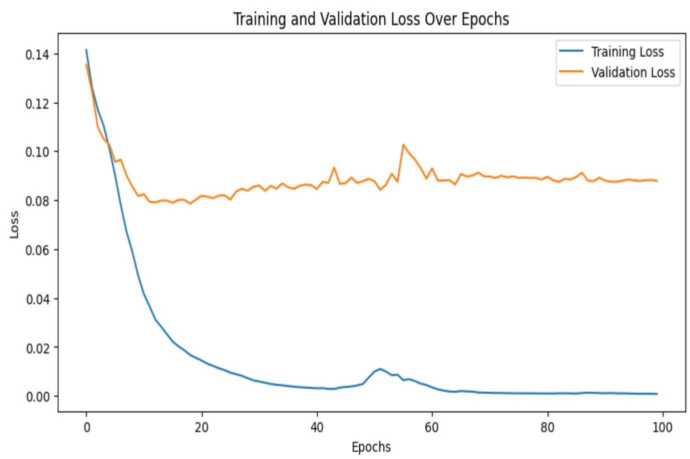


Fig. 5: Training and validation loss plots

4.2 Observations

The training loss in Fig. 5 shows a steady and noticeable drop as the epochs increase, which is a good sign that the model is learning well from the training data. The validation loss also levels off after a quick initial decline, which is reassuring as it means the model is still able to generalize well. While there are a few small fluctuations in the validation loss, they are minor and within an acceptable range, showing that the model can achieve a good balance between underfitting and overfitting.

To evaluate the performance of our proposed model, we compare it against several state-of-the-art techniques. Table 4 presents the F1-score, and AUC score

Table 4: Comparison of F1-score and AUC-Score across different models

Model	F1-score	AUC-Score
IML-ViT	0.658	0.425
TransForensics	0.627	0.674
ObjectFormer	0.579	0.758
MantraNet	0.566	0.817
PSCCNet	0.554	0.982
ProFact	0.553	0.511
SPAN	0.382	0.936
Our Model	**0.5712**	**0.7678**

for both training and testing phases, highlighting the effectiveness of our approach in comparison to existing methods.

The images were categorized based on the percentage of tampering done, and the model's performance was tested for each category. Table 5 shows the results across the different categories.

Based on observations, the model performance significantly improves when the tampering percentage exceeds 20%, indicating that the model is more effective in detecting and localizing tampered regions in images with higher levels of tampering.

Table 5: Tampering Percentage and Corresponding Number of Images

Tampering Percentage	Number of Tampering Images	F1 Score
0–20%	4444	0.4589
20–40%	528	0.8099
40–60%	310	0.8331
60–80%	29	0.8331
80–100%	10	0.8217

5 Conclusion

This study explored various existing approaches for image forgery localization and introduced a CNN-based method integrating Error Level Analysis (ELA) to detect and localize tampered regions. The proposed model demonstrated strong performance on the CASIA v2.0 dataset, achieving an F1-score of 0.5712 and an AUC-score of 0.7678, while maintaining computational efficiency compared to complex architectures like Mantra-Net and ObjectFormer. However, certain limitations remain. The model's performance decreases for low-percentage tampering (less than 20%), where subtle forgeries are harder to detect. Additionally, the approach is currently limited to JPEG-compressed images, as ELA relies on compression inconsistencies, making it less effective for high-quality lossless formats like PNG or TIFF. Another challenge is the lack of generalization to forgeries involving advanced AI-generated manipulations such as deepfakes. For future improvements, Exploring hybrid deep learning architectures that combine CNNs with transformers may further improve forgery localization accuracy. Finally, extending the model to handle scanned documents and low-quality images could make it more robust for real-world applications in forensic analysis and digital media verification.

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