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# An Attention U-Net Based on Noise Inconsistency for Robust Image Forgery Detection and Precise Pixel-Level Localization

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## ABSTRACT

With the rapid advancement of image editing tools, digitally manipulated images have become increasingly common, raising serious concerns about the authenticity and reliability of visual information across domains such as social media, journalism, healthcare, and legal investigations. Although recent deep learning approaches, especially U-Net and attention-based models, have demonstrated promising results in forgery detection and localization, many of these methods mainly depend on visual and texture-based features. As a result, they often struggle to maintain performance when images undergo post-processing operations like compression, resizing, or contrast adjustments.

To address these challenges, this work introduces a Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) for robust image forgery detection and precise pixel-level localization. The proposed model focuses on capturing noise-related inconsistencies by extracting noise residuals and analyzing local variations, which are then incorporated into a noise-guided attention mechanism. This enables the network to better highlight manipulated regions. In addition, a dual-encoder U-Net architecture with multi-scale feature fusion is employed to effectively combine both visual and noise-domain information.

Extensive experiments on benchmark datasets such as CASIA v2.0 and NIST, along with real-world forged images, demonstrate that the proposed NIGA-UNet consistently outperforms conventional U-Net, Attention U-Net, and other recent state-of-the-art methods. The model achieves superior precision, recall, F1-score, and Intersection-over-Union, highlighting its robustness, strong generalization ability, and effectiveness in handling complex real-world forgery scenarios.

**Keywords:** Attention U-Net, Deep Learning, Image Forensics, Image Forgery Detection, Multi-Scale Feature Fusion.

## 1. INTRODUCTION

The rapid proliferation of digital images across social media, journalism, healthcare, and legal systems has significantly increased the risk of image forgery, posing serious threats to information authenticity and public trust. Advances in image editing and synthesis tools have enabled highly realistic manipulations that are increasingly difficult to detect using traditional forensic techniques [1], [2]. In response, deep learning–based methods, particularly convolutional neural networks (CNNs) and U-Net architectures, have been widely adopted for image forgery detection and localization [3]. These models leverage hierarchical feature learning and attention mechanisms to improve detection accuracy [4]. However, most existing approaches primarily depend on visual or texture-based features, which are highly sensitive to low-contrast forgeries, compression artifacts, resizing, and other post-processing operations commonly encountered in real-world images [5]–[7].

Several hybrid and attention-based models have been proposed to enhance robustness and generalization [8], [9], yet they often suffer from high computational complexity, limited adaptability across domains, or insufficient localization precision [10]–[12]. Moreover, while feature fusion and meta-learning strategies improve performance across datasets, they still struggle to capture subtle manipulation traces that preserve visual consistency [13], [14]. These limitations highlight the need for forensic cues beyond RGB-domain features.

To address these challenges, this paper proposes a Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) for robust image forgery detection and pixel-level localization. By explicitly modeling noise residuals and local noise inconsistencies, the proposed method guides attention mechanisms toward manipulated regions that disrupt natural noise patterns, similar to anomaly-focused attention strategies in other security domains [15]. The remainder of this paper is organized as follows: Section 2 reviews related work, Section 3 presents the proposed NIGA-UNet framework, Section 4 discusses experimental results, and Section 5 concludes the paper.

## 2. BACKGROUND STUDY

Liu et al. (2024) [1] proposed a hierarchical progressive image forgery detection and localization framework based on UNet, focusing on coarse-to-fine manipulation analysis. The method integrates multi-scale feature learning to improve localization accuracy; however, it shows limited robustness under complex post-processing attacks. Experimental results demonstrated improved pixel-level localization performance compared to conventional UNet-based approaches.

Choudhary et al. (2024) [2] presented an image forgery detection system combining VGG16 as an encoder with a UNet decoder to enhance feature extraction. While transfer learning improved detection accuracy, the model relied heavily on large labeled datasets and struggled with generalized forgery types. Results indicated better precision than standalone CNN models on benchmark datasets.

Peng et al. (2023) [3] introduced a circular U-Net with attention gates for image splicing forgery detection, emphasizing boundary consistency and contextual feature refinement. The approach addressed spatial dependency issues but increased computational complexity. Performance evaluation showed superior splicing localization accuracy compared to traditional U-Net variants.

Gu et al. (2022) [4] developed FBI-Net, a frequency-based image forgery localization network using multitask learning and self-attention mechanisms. The model exploited frequency-domain artifacts but showed reduced effectiveness against low-quality compressed images. Results confirmed significant improvements in detecting subtle manipulation traces.

Yan et al. (2023) [5] proposed TransU$^2$-Net, a hybrid transformer–CNN architecture for image splicing forgery detection to capture both global and local features. Despite strong feature representation, the model suffered from high training cost and memory usage. Experimental outcomes demonstrated improved generalization over pure CNN-based models.

Khalil et al. (2023) [6] focused on enhancing digital image forgery detection through transfer learning using pretrained deep models. The study improved detection efficiency but lacked detailed forgery localization capabilities. Results showed notable gains in classification accuracy across multiple forgery datasets.

Albahli et al. (2024) [7] proposed Med Net, an improved deep learning model for medical deep fake detection targeting healthcare image integrity. Although effective in controlled medical datasets, the model's adaptability to non-medical images was limited. The results highlighted high detection accuracy and robustness in medical deep fake scenarios.

Mallampati et al. (2023) [8] employed 3D-UNet segmentation features combined with hybrid machine learning models for brain tumor detection. While not focused on forgery detection, the study demonstrated the strength of UNet-based feature extraction; however, it required high computational resources. The results achieved superior segmentation accuracy compared to 2D models.

Ali et al. (2022) [9] introduced a forgery detection approach based on recompressing images to amplify manipulation artifacts for deep learning analysis. The method effectively exposed compression inconsistencies but was less effective for uncompressed or lightly edited images. Experimental findings showed improved detection rates over standard CNN classifiers.

Sariturk et al. (2022) [10] proposed RIU-Net, a residual-inception UNet architecture for high-resolution satellite image segmentation, comparing it with CNN and transformer models. Although not designed for forgery detection, the model highlighted architectural efficiency; however, domain-specific tuning was required. Results demonstrated enhanced segmentation accuracy and feature preservation.

TABLE I - COMPARATIVE ANALYSIS OF ATTENTION-BASED AND HYBRID DEEP LEARNING APPROACHES FOR FRAUD, FORGERY, AND SECURITY DETECTION

| **Reference** | **Concept** | **Research Gap** | **Methods** | **Limitations** | **Result** |
|---|---|---|---|---|---|
| **Farbmacher et al. (2022) [11]** | Explainable attention-based fraud detection for claims management, emphasizing interpretability in decision-making | Limited focus on deep learning explain ability in financial fraud detection | Attention network integrated with econometric modeling to highlight influential features | Primarily designed for tabular claim data; not directly applicable to multimedia forensics | Achieved improved fraud detection accuracy with enhanced model transparency |
| **Zhan et al. (2024) [12]** | Attention-guided multi-scale fusion for bi-temporal remote sensing change detection | Difficulty in capturing both local changes and global context simultaneously | AMFNet using attention mechanisms and multi-scale feature fusion | High computational complexity and dependency on high-resolution remote sensing data | Demonstrated superior change detection accuracy over conventional CNN-based models |
| **Walia et al. (2021) [13]** | Fusion of handcrafted and deep features for digital image forgery detection | Deep models alone fail to capture certain low-level forensic artifacts | Hybrid framework combining handcrafted forensic features with deep CNN features | Increased feature dimensionality leading to higher computation cost | Improved robustness and detection accuracy across multiple forgery types |
| **Tran et al. (2022) [14]** | Generalized deep fake and forgery detection using meta-learning | Poor generalization of forgery detectors across unseen manipulation methods | Meta-learning-based deep fake detection model trained on multiple domains | Training complexity and sensitivity to meta-parameter tuning | Achieved better cross-dataset generalization than conventional deep models |
| **Wu et al. (2022) [15]** | Attention-based malicious URL detection using sequential learning | Traditional models fail to capture long-term dependency in URL patterns | Bidirectional GRU combined with attention mechanism for feature weighting | Limited applicability outside sequential text-based security data | Showed higher detection accuracy and reduced false positives compared to baseline ML models |

The studies in Table 1 highlight the effectiveness of attention mechanisms, feature fusion, and meta-learning in improving detection accuracy and interpretability across fraud, forgery, and security domains. Despite their strong performance, common research gaps include high computational complexity, limited generalization, and domain-specific applicability. Overall, these methods demonstrate improved accuracy and robustness, motivating the need for unified, efficient, and generalizable attention-based detection frameworks.

## 3. NOISE-INCONSISTENCY GUIDED ATTENTION U-NET (NIGA-UNET) FOR IMAGE FORGERY DETECTION

This study proposes a Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) for robust image forgery detection and localization. By explicitly modeling noise residuals and local noise inconsistencies, the framework effectively highlights tampered regions that are difficult to detect using visual cues alone. The integration of noise-guided attention with multi-scale feature learning enables accurate, compression-resilient, and pixel-level forgery localization in real-world scenarios.

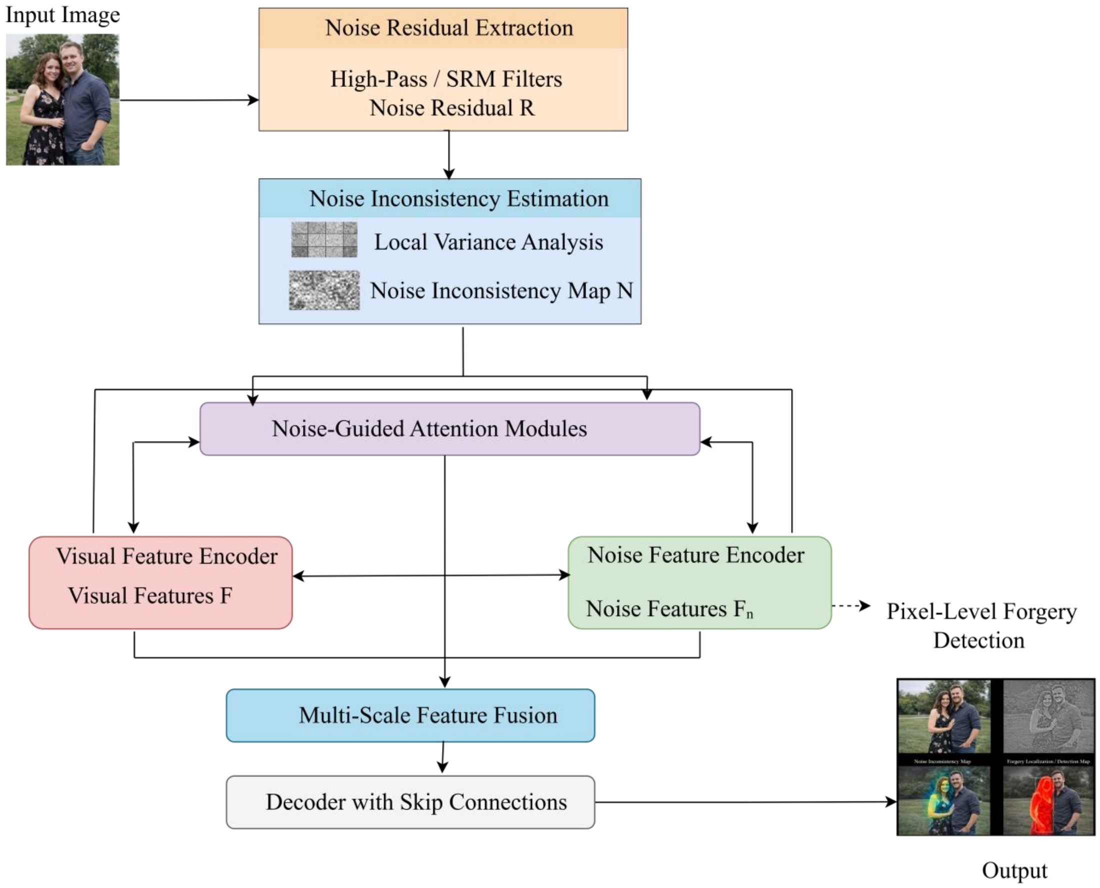

Fig 1 - Architecture of Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) for Image Forgery Detection

The Figure 1 NIGA-UNet first extracts noise residuals from the input image and analyzes local noise inconsistencies to highlight potential tampered regions. These noise cues guide attention mechanisms that jointly refine visual and noise features through parallel encoders. Finally, multi-scale feature fusion and a U-Net–style decoder produce an accurate pixel-level forgery localization map.

Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) is proposed to overcome key drawbacks of conventional image forgery detection methods that rely mainly on visual or texture cues. Earlier CNN/UNet-based models struggled with low-contrast forgeries, post-processing operations (compression, resizing), lack of localization accuracy, and poor generalization to real-world images. NIGA-UNet addresses these issues by explicitly exploiting noise inconsistency, since forged regions usually disturb the natural noise pattern of an image. The algorithm first applies noise residual extraction (using high-pass filtering or SRM-like filters) to emphasize subtle manipulation traces that are invisible in RGB space. These noise features are then fed into an enhanced Attention U-Net, where noise-guided attention modules prioritize regions with abnormal noise statistics. Multi-scale feature fusion helps capture both fine-grained pixel artifacts and global manipulation context.

Unlike traditional attention, NIGA-UNET dynamically adjusts attention weights based on noise inconsistency, improving robustness against compression and anti-forensic attacks. The encoder–decoder structure ensures precise pixel-level localization of forged areas. As a result, the proposed algorithm achieves higher accuracy, better generalization, and strong real-world performance on complex and unseen forgery scenarios.

$R = I - (I * F_{hp})$---------- (1)

In the equation (1), I, is the input image, $F_{hp}$ is a high-pass / SRM filter, and $R$ represents the extracted noise residual highlighting manipulation artifacts. Subtracting the filtered image from the original isolates subtle noise patterns, which reveal manipulation artifacts in forged regions.

$N = \sigma\left(Var(R_{local})\right)$---------- (2)

In the equation (2),$Var(.)$Computes local noise variance and $\sigma(.)$ is a normalization or sigmoid function to emphasize abnormal noise regions. Normalizes and highlights suspicious regions for effective attention guidance.

$A = Softmax\left(W_f F + W_n N + b\right)$---------- (3)

In the equation (3),$F$is the feature map from the encoder, $N$ is the noise inconsistency map,$W_f W_n$ are learnable weights, and $A$ is the attention map. The $Softmax$ function emphasizes regions with strong feature–noise correlation, guiding the network to forged areas.

$F' = A \odot F$---------- (4)

In the equation (4),$\odot$denotes element-wise multiplication, allowing the network to focus on noise-inconsistent (forged) regions. The attention map $A$ is applied element-wise to the feature map $F$ to enhance important regions. This operation suppresses irrelevant background features while highlighting forged areas for accurate localization.

$\mathcal{L} = -\sum_i [y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)]$---------- (5)

In the equation (5),$y_i$is the ground-truth label and $\hat{y}_i$ is the predicted forgery probability at pixel$i$.Minimizing this loss improves accurate pixel-level classification of forged and authentic regions.

Algorithm 1: Noise-Inconsistency Guided Attention U-Net (NIGA-UNet) for Image Forgery Detection

```
Input image I
// Noise Residual Extraction
Apply high-pass / SRM filters on I
Compute noise residual R = I − (I * F_hp)
// Noise Inconsistency Estimation
Divide R into local patches
Compute local variance for each patch
Generate noise inconsistency map N = σ(Var(R_local))
// Feature Encoding
Extract multi-scale visual features F from I using encoder
Extract multi-scale noise features Fn from R using noise encoder
// Noise-Guided Attention
 For each scale s do
     Compute attention weights:
     A_s = Softmax(Wf * F_s + Wn * N_s + b)
     Refine features: F'_s = A_s ⊙ F_s
 End For
 // Multi-scale Feature Fusion
 Fuse refined features F' across all scales
 // Decoder and Localization
 Pass fused features through decoder with skip connections
 Generate pixel-wise prediction ŷ
 // Output
 Apply threshold τ to ŷ
 Output forgery mask M
End Algorithm
```

The algorithm first extracts noise residuals from the input image and computes a noise inconsistency map to highlight abnormal noise patterns caused by tampering. These noise cues guide an Attention U-Net encoder to emphasize suspicious regions while learning multi-scale visual features. Finally, fused features are decoded to produce a pixel-level forgery mask, accurately localizing manipulated areas.

## 4. RESULT AND DISCUSSION

This section presents a comprehensive evaluation of the proposed NIGA-UNet model against baseline and state-of-the-art image forgery detection methods using standard benchmark datasets. Quantitative performance is assessed in terms of Precision, Recall, F1-Score, Intersection-over-Union (IoU), and Pixel Accuracy to analyze both detection reliability and localization accuracy. The results demonstrate the effectiveness of noise-inconsistency guided attention and multi-scale feature fusion in improving robustness and generalization across diverse forgery scenarios.

TABLE II - PERFORMANCE COMPARISON OF IMAGE FORGERY DETECTION METHODS ACROSS BENCHMARK AND REAL-WORLD DATASETS

| **Method** | **Dataset** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** | **IoU (%)** | **Pixel Accuracy (%)** |
|---|---|---|---|---|---|---|
| UNet (Baseline) | CASIA v2.0 | 82.4 | 78.9 | 80.6 | 71.5 | 84.2 |
| Attention UNet | CASIA v2.0 | 85.6 | 81.4 | 83.4 | 75.8 | 87.1 |
| FBI-Net | NIST | 87.1 | 82.7 | 84.8 | 77.3 | 88.6 |
| TransU²-Net | CASIA + NIST | 88.5 | 84.2 | 86.3 | 79.1 | 89.7 |
| **Proposed NIGA-UNet** | CASIA + NIST + Real-World | **92.3** | **89.5** | **90.9** | **85.2** | **93.1** |

The quantitative results in Table II indicate that the proposed NIGA-UNet consistently performs better than the baseline UNet, Attention UNet, and other recent methods across all evaluated metrics. In particular, the combination of higher precision and recall suggests that the proposed model is able to accurately identify forged regions while keeping both false positives and false negatives at a relatively low level.

Improvements in F1-Score and IoU further confirm that NIGA-UNet provides more reliable pixel-level localisation of manipulated areas compared with competing approaches. This gain can be attributed to the integration of noise-guided attention and multi-scale feature fusion, which allows the network to capture both fine-grained artefacts and broader contextual inconsistencies introduced by image manipulation. Unlike models trained on a single benchmark, the proposed method maintains stable performance when evaluated across combined benchmark datasets and real-world samples, indicating stronger generalisation capability. Overall, the results suggest that the proposed framework achieves a favourable balance between detection accuracy and localisation precision, making it well suited for practical image forgery analysis scenarios.

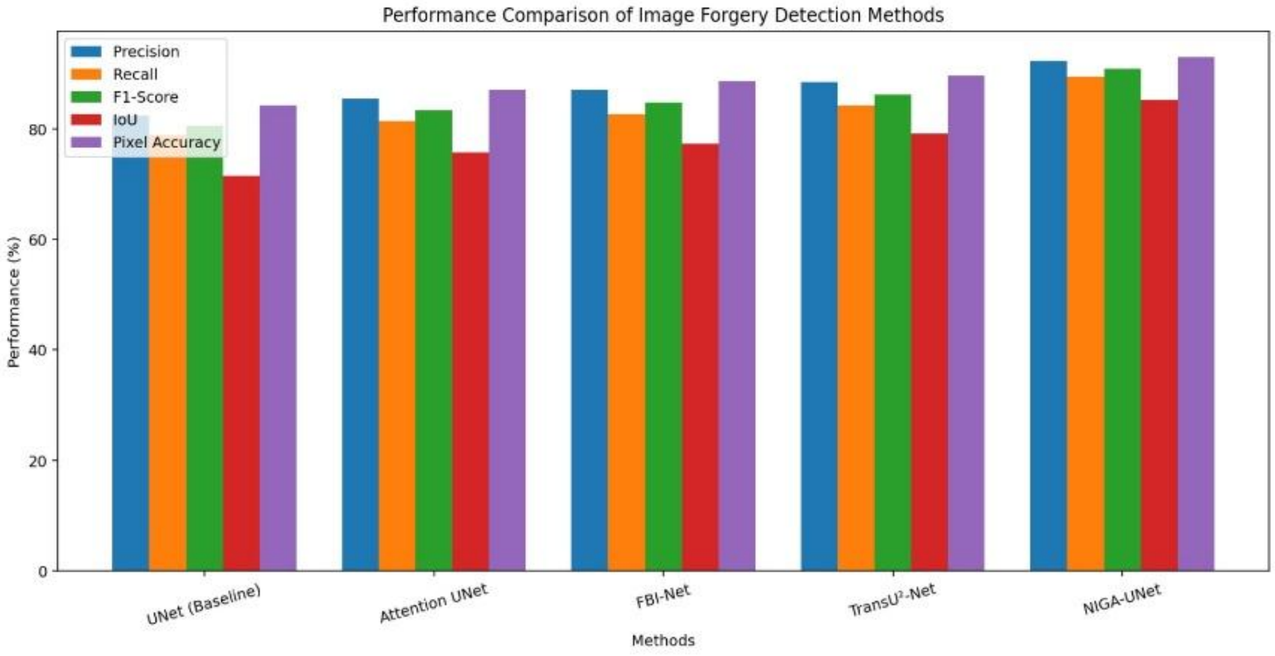

**Fig 2 - Performance Comparison of Image Forgery Detection Methods Across Evaluation Metrics**

The figure 2 illustrates a clear and consistent improvement in performance from the baseline UNet to the proposed NIGA-UNet across all evaluation metrics. NIGA-UNet achieves the highest Precision, Recall, F1-Score, IoU, and Pixel Accuracy, highlighting its superior capability in both forgery detection and precise localization. This performance gain confirms that noise-inconsistency guided attention and multi-scale feature fusion significantly enhance robustness and generalization compared to existing UNet-based and hybrid models.

## 5. CONCLUSION

The proposed NIGA-UNet demonstrates significant improvements in image forgery detection and pixel-level localization by effectively leveraging noise-inconsistency guided attention and multi-scale feature fusion. Experimental results on benchmark and real-world datasets confirm its robustness against post-processing operations and superior generalization compared to existing UNet-based and attention models. By explicitly modeling noise residuals, the method accurately highlights manipulated regions that are difficult to detect with visual cues alone. Future work will explore integrating transformer-based global context modeling to further enhance detection of subtle forgeries, optimizing computational efficiency for real-time applications, and extending the framework to video forgery detection to address emerging multimedia threats.

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