IMAGE TAMPERING DETECTION AND LOCALIZATION USING DEEP LEARNING TECHNIQUES

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BONAFIDE CERTIFICATE

Certified that this project report titled **IMAGE TAMPERING DETECTION AND LOCALIZATION USING DEEP LEARNING TECHNIQUES** is the *bonafide* work of **JOTHI SRI S (2022103049)**, **KEERTHIKA B (2022103552)** , **NALINIKSHA P (2022103553)** and **PUNITHA K (2022103561)** who carried out the project work under my supervision, for the fulfillment of the requirements for the award of the degree of Bachelor of Engineering in Computer Science and Engineering. Certified further that to the best of my knowledge, the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or an award was conferred on an earlier occasion on these or any other candidates.

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Jothi Sri S **Keerthika B** **Naliniksha P** **Punitha K**

ABSTRACT – ENGLISH

The rapid growth in advanced editing and generative technologies has made manipulations of digital images fairly common. It is tough to detect visually plausible tampered images when the manipulations are subtle or when they are smoothly blended into the background. Though deep learning–based methods have improved on manipulation detection, most of the existing approaches fail to effectively exploit boundary inconsistencies.

This work presents an image tampering detection and localization framework, deep learning-based, with a focus on boundary-aware feature learning. The model uses a ResNet-50 encoder for extracting multiscale representations, decoder to introduce hybrid attention and boundary-aware attention modules in order to underline irregularities along manipulated boundaries. The boundary-guided contrastive loss is developed to impose stronger feature separation so that the network can learn more discriminative and robust representations under multiscale supervision.

In this paper, the framework will be implemented in PyTorch and evaluated on benchmark datasets. The expected results are anticipated to demonstrate improved boundary sharpness, mask completeness, and robustness compared to existing methods, particularly in complex scenes with subtle manipulations. These outcomes are expected to highlight the effectiveness of integrating boundary-aware attention mechanisms with contrastive learning for accurate image tampering localization.

ABSTRACT – TAMIL

மேம்பட்ட தொகுப்பு மற்றும் உருவாக்கத் தொழில்நுட்பங்களின் வேகமான வளர்ச்சி, டிஜிட்டல் பட மாற்றங்களை அதிகரித்துள்ளது. மாற்றங்கள் நுணுக்கமாக அல்லது பின்னணியில் மென்மையாக கலந்திருக்கும் போது, பார்வைக்கு நம்பத்தகுந்த மாற்றப்பட்ட படங்களை கண்டறிதல் சவாலாகிறது. ஆழக் கற்றல் அடிப்படையிலான முறைகள் முன்னேற்றம் கண்டுள்ளன என்றாலும், பல தற்போதைய அணுகுமுறைகள் எல்லை முரண்பாடுகளை பயனுள்ளதாகப் பயன்படுத்துவதில் தோல்வியடைந்துள்ளன.

இந்த ஆய்வு, எல்லை-அறிவு அம்சக் கற்றலுக்கு முக்கியத்துவம் அளிக்கும் ஆழக் கற்றல் அடிப்படையிலான பட மாற்றம் கண்டறிதல் மற்றும் உள்ளூர் நிர்ணய வடிவமைப்பை முன்வைக்கிறது. பலஅளவிலான பிரதிநிதித்துவங்களைப் பெற ResNet-50 என்கோடரைப் பயன்படுத்தி, கலப்பு மற்றும் எல்லை-அறிவு கவனிப்பு கூறுகளுடன் கூடிய டிகோடர் வடிவமைக்கப்பட்டுள்ளது. வலுவான அம்சப் பிரிவை மேம்படுத்த எல்லை வழிகாட்டப்பட்ட மாறுபாட்டுக் கற்றல் இழப்பு பயன்படுத்தப்படுகிறது.

இந்த வடிவமைப்பு PyTorch-ல் செயல்படுத்தப்பட்டு, நிலையான தரவுத்தொகுதிகளில் மதிப்பாய்வு செய்யப்படுகிறது. எல்லைத் தெளிவு, முகமூடி முழுமை மற்றும் வலிமை ஆகியவற்றில் தற்போதைய முறைகளைவிட மேம்பட்ட செயல்திறன், குறிப்பாக நுணுக்கமான மாற்றங்கள் உள்ள சிக்கலான காட்சிகளில், எதிர்பார்க்கப்படுகிறது. இது எல்லை-அறிவு கவனிப்பும் மாறுபாட்டுக் கற்றலும் ஒருங்கிணைக்கப்படும் போது பட மாற்றம் உள்ளூர் நிர்ணயம் மேலும் துல்லியமாகும் என்பதை வலியுறுத்துகிறது.

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LIST OF ABBREVIATIONS

AUC Area Under Curve

BAM Boundary-Aware Attention Module

BCL Boundary-Guided Contrastive Learning

BF1 Boundary F1-Score

BIoU Boundary Intersection over Union

CASIA Chinese Academy of Sciences Image Dataset

CNN Convolutional Neural Network

DL Deep Learning

GAN Generative Adversarial Network

HAM Hybrid Attention Module

IoU Intersection over Union

MAE Mean Absolute Error

MCC Matthews Correlation Coefficient

PR-AUC Precision–Recall Area Under Curve

ResNet Residual Network

RGB Red Green Blue

SGD Stochastic Gradient Descent

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Digital image manipulation has become increasingly accessible and realistic thanks to the rapid improvement of image editing software and AI-driven generative models. Splicing, copy–move, object removal, and inpainting can now be performed even by unskilled users, making altered visual content nearly imperceptible to human observers. While these tools enhance creativity in multimedia production, they also pose serious risks when misused for misinformation, cybercrime, or evidence fabrication. Hence, image manipulation detection and localization has emerged as a crucial research area within digital forensics and computer vision.

Traditional forensic methods rely on handcrafted features such as noise inconsistencies, chromatic aberrations, illumination clues, or JPEG compression artifacts. However, these techniques often fail when manipulations are subtle, when image textures are complex, or when strong post-processing (e.g., resizing, filtering, or compression) conceals forensic traces. Deep learning methods have therefore become the dominant solution, offering the ability to learn manipulation cues directly from data. Recent studies emphasize that boundary information plays a vital role because boundary inconsistencies remain one of the strongest indicators of tampering. Nevertheless, detecting these boundaries is still challenging since natural edges can appear similar to tam-

pered ones, often leading to false positives and weak generalization. Several recent works demonstrate that encoder–decoder architectures enhanced with boundary-aware attention and contrastive learning mechanisms can capture subtle tampering artifacts more effectively [10, 4, 8].

1.2 PROBLEM STATEMENT

Most digital images may contain manipulations that are nearly indistinguishable from authentic content. This research therefore focuses on designing a system capable of not only identifying the presence of tampering but also accurately localizing manipulated pixels at fine granularity. The goal is to identify tampered regions, learn discriminative features that separate authentic from falsified content, and reduce false classifications along natural boundaries. The key challenges include diverse manipulation types, inconsistent artifacts across datasets, varied natural textures, and the subtle traces left by advanced generative models. A robust solution must integrate strong feature extraction, boundary-aware refinement, and contrastive representation learning to distinguish tampered boundaries from natural structures.

1.3 OBJECTIVES

The major objectives of this thesis are as follows:

- Implement a baseline encoder–decoder architecture using a ResNet-50 backbone integrated with a Boundary-Aware Module (BAM) and boundary-guided contrastive loss for improved pixel-level localization.
- Design a dual-branch refinement module to differentiate between natural and tampered boundaries using pseudo-labels derived from edge detectors.
- Include an image-level classification module to predict whether

an image is authentic or manipulated, complementing pixel-level predictions.

- Evaluate the proposed system on benchmark datasets such as CASIA v1/v2, Columbia, Coverage, and IMD2020. Performance will be measured using IoU, F1-score, accuracy, AUC, and boundary-based metrics.
- Conduct ablation studies to assess the contribution of each enhancement, including contrastive learning and dual-branch refinement.

1.4 CHALLENGES AND APPLICATIONS

Despite advances in deep learning, several challenges persist in tampering localization. Subtle manipulations often leave minimal traces, and natural edges may be mistaken for tampered ones. Lighting variations, complex textures, compression artifacts, and diverse manipulation types further complicate detection. Moreover, models trained on one dataset often fail to generalize to others due to domain discrepancies.

Accurate image tampering detection has a broad range of applications:

- **Digital Forensics:** Assisting law enforcement in verifying the authenticity of digital evidence.
- **Media Verification:** Enabling fact-checking organizations to identify manipulated online content.
- **Journalism:** Preserving the integrity of published visual information.
- **Social Media Monitoring:** Supporting automated systems that flag manipulated content to combat misinformation.
- **Security and Surveillance:** Preventing unauthorized alteration of

critical visual data.

1.5 ORGANIZATION OF THE THESIS

The thesis is organized into seven chapters as follows:

- **Chapter 1 – Introduction:** Outlines the research background, problem statement, objectives, challenges, and applications of image tampering detection.
- **Chapter 2 – Literature Survey:** Reviews previous works and highlights existing gaps in image manipulation detection and localization.
- **Chapter 3 – Requirements Analysis:** Presents the hardware, software, and dataset requirements, along with system analysis for model development.
- **Chapter 4 – System Design:** Describes the proposed architecture and submodules, including preprocessing, encoder (ResNet-50), decoder with BAM, and other refinement modules.
- **Chapter 5 – Implementation Details:** Explains dataset loading, feature extraction, and the integration of HAM and Boundary-Aware Decoder modules.
- **Chapter 6 – Results and Discussions:** Provides experimental results, performance evaluation, and analysis on multiple benchmark datasets.
- **Chapter 7 – Conclusions and Future Work:** Summarizes key findings and suggests directions for further research and model improvement.

CHAPTER 2

LITERATURE SURVEY

2.1 RELATED WORKS

Image tampering detection and localization has witnessed remarkable progress with the rise of deep learning. Early forensic techniques relied on handcrafted cues such as color filter array inconsistencies, JPEG block artifacts, illuminant irregularities, and noise statistics. However, as modern editing and generative tools blend manipulations seamlessly into surrounding textures, traditional methods often fail to detect them. Recent deep learning approaches learn manipulation features directly from data using encoder–decoder architectures, attention mechanisms, and contrastive feature learning. Major advances and their respective limitations are summarized below.

CFL-Net: Contrastive Learning for Pixel-Level Localization

CFL-Net integrates supervised contrastive loss with cross-entropy loss to better separate tampered and non-tampered region embeddings. It also fuses RGB and noise-residual features to enhance localization accuracy. Although effective in improving feature discrimination, it lacks a dedicated attention mechanism for refining manipulation boundaries, which limits performance when manipulations are subtle or edges are weak [10].

ObjectFormer: Transformer-Based Manipulation Localization

ObjectFormer [5] introduces a transformer framework that fuses RGB and high-frequency features for extracting object-level semantics during tampering detection. Learnable object prototypes are used in a stacked encoder–decoder design to refine predictions progressively. While powerful, its success strongly depends on the quality of extracted high-frequency components, and without explicit boundary modeling, robustness declines against unseen manipulations or cross-domain data.

Deep Segmentation and Encoder–Decoder Architectures

Several studies have explored generic deep segmentation architectures that inspire manipulation localization. For example, [3] reviews deep neural designs for semantic segmentation in medical imaging, highlighting the effectiveness of encoder–decoder networks with multi-scale fusion. Similarly, SegNetRes-CRF [1] employs a convolutional encoder–decoder model with conditional random fields to preserve edge structure and refine segmentation boundaries. These concepts strongly influence the boundary refinement strategies used in modern tampering localization frameworks.

Multi-View Multi-Scale Supervision

Multi-view multi-scale frameworks [7] combine feature extraction from noise, edge, and RGB domains with multi-scale supervision to enhance robustness across manipulation types. They leverage multi-level edge cues for refinement but, without explicit boundary-attention modules, struggle to detect finely blended or low-contrast edges.

Contrastive and Semantic Feature Integration

Contrastive feature learning has also been applied to degraded image segmentation tasks. Dong et al. [2] proposed intra- and inter-image contrastive learning to improve degraded image semantic segmentation, demonstrating that contrastive objectives can strengthen feature representation and class separation. This approach provides theoretical grounding for applying contrastive learning to tampering localization, where separating authentic and manipulated features is equally crucial.

Boundary-Aware Attention and Contrastive Learning (Base Paper)

The base paper proposes a boundary-guided framework combining attentive feature fusion with contrastive representation learning. A Boundary-Aware Attention Module (BAM) extracts high-frequency boundary features by correlating encoder skip connections with decoder features. A Boundary-Guided Contrastive Loss then separates tampered and non-tampered embeddings in boundary regions, improving localization accuracy. Despite these advances, false positives persist along natural edges where the model confuses real and tampered boundaries [4].

Pixel-Inconsistency and Feature-Enhancement Models

Recent models, including SPAN, SC-Fusion, and pixel-inconsistency modeling, focus on enhancing spatial–channel interactions or fine-grained texture inconsistencies [9, 6]. Although these methods improve mask completeness, they lack explicit boundary discrimination mechanisms, leading to edge-level ambiguity in high-texture or dense regions.

2.2 GAPS IDENTIFIED

Despite considerable advancements, several consistent weaknesses are observed across existing works:

- **Lack of precise boundary differentiation:** Most models struggle to distinguish natural edges from altered boundaries. Even boundary-aware methods continue to confuse genuine and tampered edges [4].
- **Insufficient feature discrimination near boundaries:** Previous contrastive frameworks sample negatives too broadly and ignore boundary regions, limiting their ability to separate subtle manipulation traces.
- **Limited generalization across datasets:** Models often perform well on training datasets but poorly in cross-dataset evaluation (e.g., CASIA → NIST16 or Columbia) due to manipulation style and compression differences.
- **Weak handling of subtle manipulations:** When tampered areas closely resemble real textures (e.g., copy–move forgeries), detection fails without explicit boundary modeling.
- **Over-reliance on RGB cues:** Several frameworks omit multi-domain fusion (noise, frequency), reducing robustness when RGB inconsistencies are minimal.
- **High false positives in textured regions:** Shadows, object outlines, and dense textures often trigger false alarms resembling manipulation discontinuities.
- **Lack of integration between image-level and pixel-level tasks:** Global classification can improve contextual awareness and prevent over-segmentation, yet many systems overlook it.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 INTRODUCTION

Requirement analysis is a critical phase in any software development or research project. It involves identifying and documenting both the functional and non-functional requirements that define the project's objectives and constraints. In this work, the goal is to design and implement a deep learning-based image tampering detection and localization system that can automatically identify and highlight manipulated regions in digital images. This chapter outlines the requirements that guided the development of the proposed system.

3.2 SYSTEM OBJECTIVES

The main objectives of this system are as follows:

- To detect whether a given digital image has been tampered with or not.
- To accurately localize the manipulated regions within an image using pixel-level segmentation.
- To enhance the model's focus on boundary inconsistencies between tampered and authentic regions using attention mechanisms.
- To improve the discriminative learning of tampered and non-tampered features through contrastive loss.
- To evaluate the system's performance using standard benchmark

datasets and relevant metrics.

3.3 SYSTEM REQUIREMENTS

The system requirements are broadly classified into two categories: **functional** and **non-functional** requirements, which define what the system does and how it performs, respectively.

3.3.1 Functional and Non-Functional Requirements

Functional Requirements:

1. **Image Input Module:** Accept input images of different formats such as JPEG and PNG for analysis.
2. **Feature Extraction:** Use a pre-trained deep neural network (ResNet-50) to extract multiscale features from the input image.
3. **Boundary-Aware Attention:** Apply hybrid attention and boundary-aware attention modules to focus on regions of interest.
4. **Tampering Localization:** Generate pixel-wise tampering masks that highlight manipulated areas.
5. **Result Visualization:** Display the detected tampered regions overlaid on the original image.
6. **Model Evaluation:** Compute accuracy, precision, recall, F1-score, and Intersection-over-Union (IoU) metrics.

Non-Functional Requirements:

- **Performance:** The system should process each image efficiently with minimal inference time.
- **Scalability:** The framework should handle large datasets and varying image resolutions effectively.
- **Usability:** The interface should be user-friendly, allowing users to easily upload and test images.
- **Reliability:** The system should produce consistent results across

different datasets.

- **Maintainability:** The implementation should be modular, reusable, and well-documented for further research.

3.3.2 Hardware and Software Requirements

Hardware Requirements:

- Processor: Intel Core i7 or higher / AMD Ryzen 7 or equivalent
- RAM: Minimum 16 GB
- GPU: NVIDIA GTX 1660 or higher (with CUDA support)
- Storage: At least 1 TB HDD or 256 GB SSD
- Operating System: Windows 11 / Ubuntu 20.04

Software Requirements:

- Programming Language: Python 3.8 or above
- Deep Learning Framework: PyTorch / TensorFlow
- Libraries: NumPy, OpenCV, Matplotlib, scikit-learn
- IDE: Jupyter Notebook / Visual Studio Code
- Dataset: CASIA v2, Columbia Uncompressed, Coverage, and IMD2020

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

The architecture of the proposed Image Tampering Detection and Localization system is built as a multistage deep learning pipeline aimed at identifying manipulated areas with high accuracy and clear boundary definition. It follows a modular encoder–decoder design enhanced with specialized boundary-focused components and contrastive learning strategies. By combining low-level texture details, high-frequency edge information, and multi-scale semantic features, the system achieves precise and reliable tamper localization.

The process begins with the **Preprocessing Module**, which standardizes the input images and generates auxiliary boundary maps for training. The **ResNet-50 Encoder** then extracts hierarchical features that represent texture, structure, and contextual information. These features are passed to the **Boundary-Aware Decoder**, where each stage uses a **Boundary-Aware Attention Module (BAM)** to emphasize boundary pixels, as these often contain tampering clues.

To better differentiate between natural and tampered boundaries, the **Dual-Branch Boundary Refinement Module** separates semantic object features from boundary features, helping to reduce false positives. The system also integrates a **Boundary-Guided Contrastive Learning Module** that enforces a clear separation between tampered and non-tampered pixels, particularly around edges.

Finally, the **Image-Level Adaptation Head** determines whether an image is authentic or manipulated, aiding the decoder by providing contextual understanding during mask prediction. Collectively, these modules form a robust architecture capable of generating sharp, accurate, and dependable tampering masks.

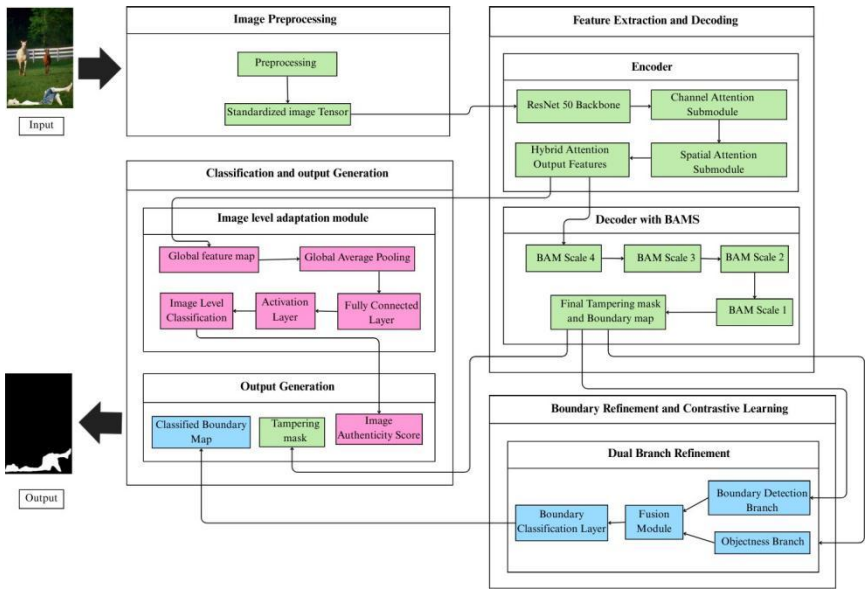


Figure 4.1 Overall system architecture.

4.2 PROPOSED SYSTEM

The proposed framework addresses key challenges in tampering localization, such as faint manipulation traces, confusion between real and fake boundaries, poor cross-dataset generalization, and instability in low-quality or compressed images. To overcome these issues, the system adopts a boundary-driven deep learning approach that combines multi-scale feature extraction, attention mechanisms, and contrastive representation learning.

The workflow starts with image preprocessing and boundary generation. The processed image is then passed to the ResNet-50 encoder, which extracts hierarchical features. These features undergo boundary-

aware decoding to reconstruct a high-resolution tampering mask. During decoding, attention mechanisms highlight subtle high-frequency differences, while the dual-branch refinement module separates authentic edges from artificial ones, resulting in sharper boundaries.

Additionally, the boundary-guided contrastive learning approach pushes features of tampered regions away from nearby non-tampered regions, improving the system's ability to discriminate fine manipulations. The final output includes a refined tampering mask, an accurate boundary map, and an overall authenticity score for the image.

This integrated design ensures high detection accuracy, strong boundary localization, and improved generalization across datasets.

4.3 SUBMODULES OF THE PROPOSED SYSTEM

4.3.1 Preprocessing Module

The preprocessing module performs essential input transformations before feeding images to the encoder. Each image is resized to 512×512, normalized using ImageNet statistics, and converted into tensor format. Ground-truth masks are binarized, and boundary maps are generated using morphological operations like dilation and subtraction.

To increase robustness, data augmentation techniques such as random flips, scaling, and color adjustments are applied. The resulting boundary ground truth serves as a key supervision signal for both the Boundary-Aware Attention and Contrastive Learning modules.

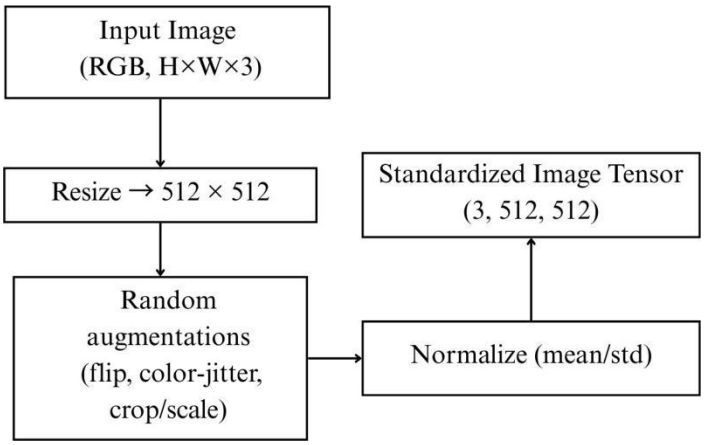


Figure 4.2 Workflow of the preprocessing module, including mask and boundary generation.

4.3.2 Encoder Module (ResNet-50 Feature Extraction)

The encoder uses the ResNet-50 architecture due to its strong capability for extracting hierarchical visual features. It produces four feature maps (C2, C3, C4, C5), each capturing a different level of information:

- C2: fine textures and noise patterns,
- C3: mid-level structural contours,
- C4: object-level semantics,
- C5: deep contextual information.

These multi-scale features retain crucial information for both mask reconstruction and boundary detection and can be further enhanced using lightweight attention layers.

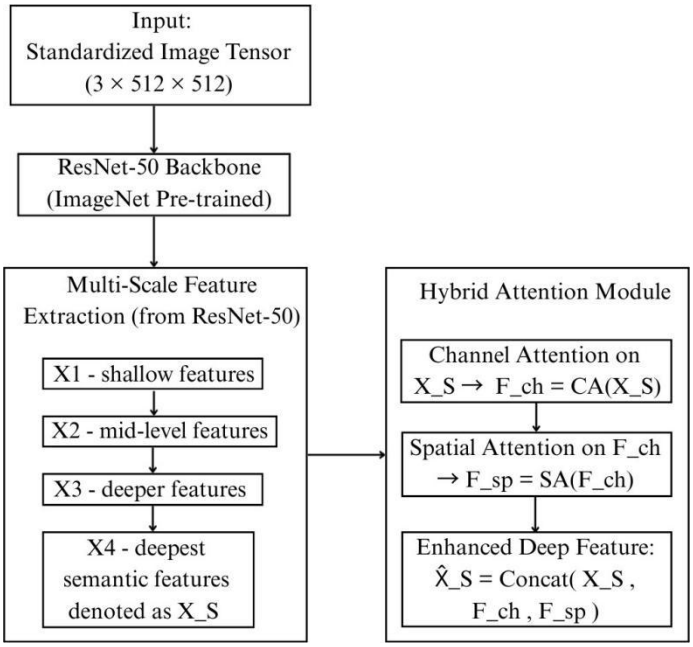


Figure 4.3 ResNet-50 encoder structure illustrating multi-scale feature extraction.

4.3.3 Decoder with Boundary-Aware Attention Module (BAM)

The decoder upsamples and fuses encoder features to form high-resolution tampering masks. Each stage of decoding integrates a Boundary-Aware Attention Module (BAM) that sharpens focus on boundary details. BAM performs the following operations:

- Local edge detection using convolutional kernels,
- Selection of top-K candidate boundary pixels,
- Cross-attention alignment between encoder and decoder features,
- Scatter-and-fuse refinement for highlighting actual manipulation edges.

This process amplifies subtle tampering traces that often hide within edge textures.

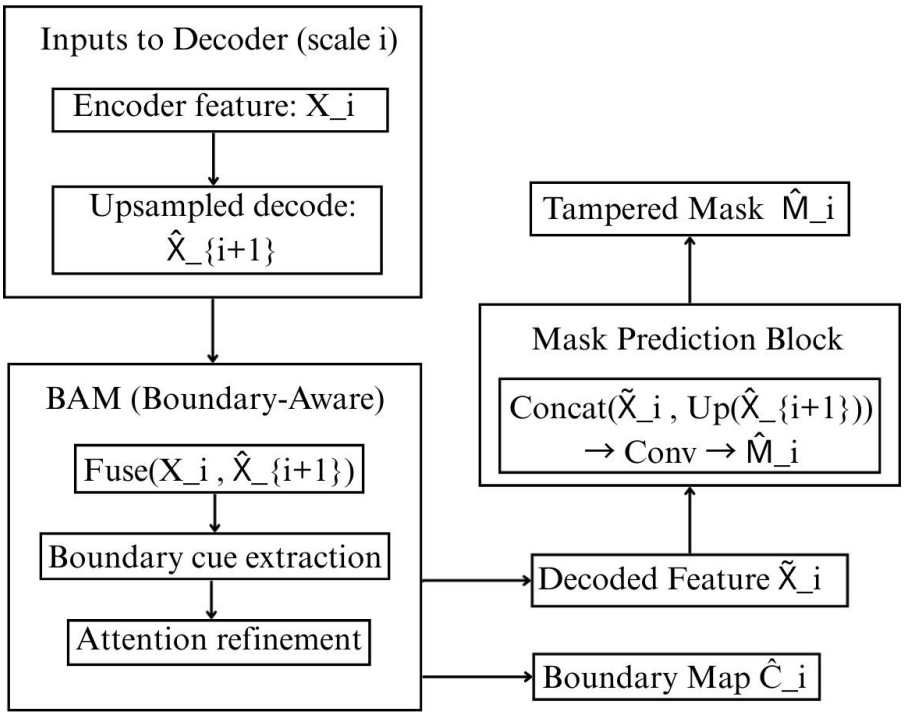


Figure 4.4 Decoder structure with Boundary-Aware Attention Module.

4.3.4 Dual-Branch Boundary Refinement Module

Since not every edge indicates manipulation, this module minimizes false positives by dividing the feature map into two branches:

- **Boundary Branch:** focuses on high-frequency discontinuities,
- **Texture/Region Branch:** captures object-level semantics and regional context.

The two outputs are then fused to produce refined boundary representations that effectively distinguish real from tampered edges.

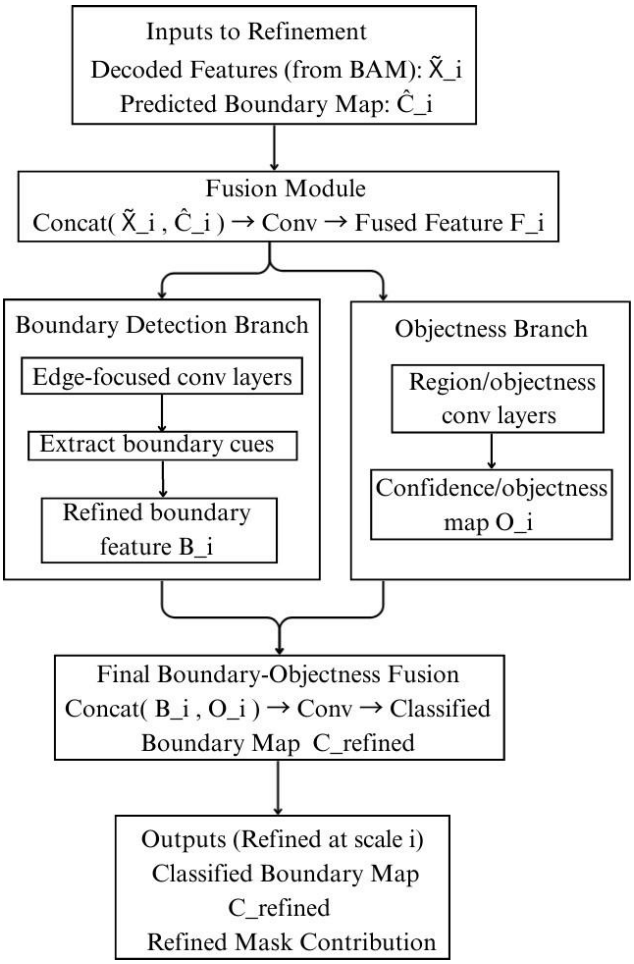


Figure 4.5 Dual-Branch Boundary Refinement Module.

4.3.5 Boundary-Guided Contrastive Learning Module

This component conducts pixel-wise contrastive learning specifically on boundary regions. Positive samples come from tampered zones, while negative samples are taken from a narrow band around boundaries. This design encourages the model to differentiate tampered and authentic features within the learned feature space.

It significantly enhances the model's ability to localize subtle manipulations, even when fake textures closely resemble real ones.

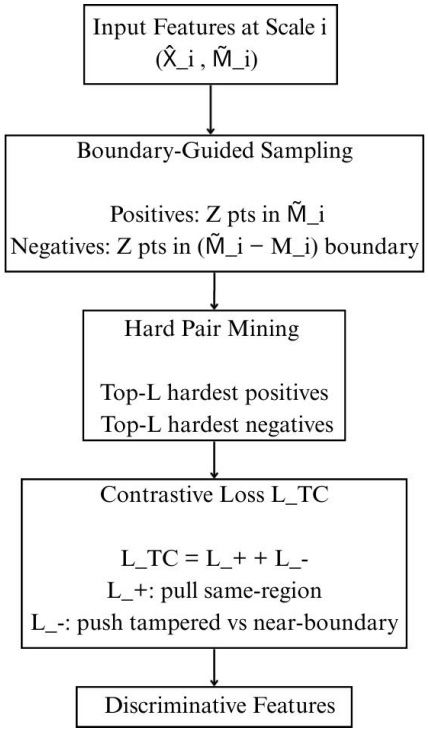


Figure 4.6 Boundary-Guided Contrastive Learning sampling strategy.

4.3.6 Image-Level Adaptation Module

The final module assesses whether an entire image is genuine or tampered. It processes deep decoder features using a lightweight convolutional head followed by global average pooling. This global classification step:

- Enhances contextual understanding,
- Minimizes false-positive predictions,
- Stabilizes output for unmanipulated images.

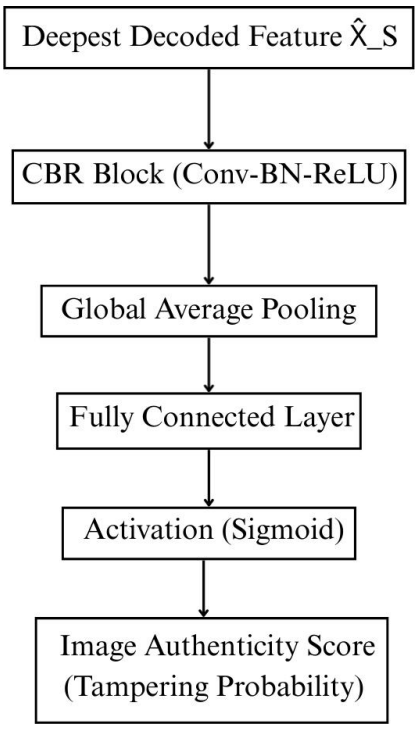


Figure 4.7 Image-Level Adaptation Module for global authenticity prediction.

In this chapter, the complete system design for image tampering detection and localization was presented. Each module-from preprocessing to image-level adaptation—was carefully structured to enhance both detection accuracy and boundary precision. The proposed architecture integrates deep feature extraction, boundary-aware attention, and contrastive learning to achieve robust performance across diverse datasets. This modular and boundary-centric design lays the foundation for effective implementation and evaluation, which are discussed in the following chapter.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 INTRODUCTION

This chapter presents the initial phase (20%) of the implementation of the proposed Image Tampering Detection and Localization framework. The implemented modules include dataset loading and preprocessing, multi-scale feature extraction using ResNet-50, the Hybrid Attention Module (HAM), and the Boundary-Aware Decoder (BAM) with preliminary refinement functionality. All components were implemented in Python using the PyTorch framework, with experiments conducted on the CASIA v2.0 dataset for training and validation.

5.2 CASIA2 DATASET LOADING AND TRANSFORMATION

The CASIA2 dataset is employed as the primary source for model training and testing. It contains authentic and tampered images along with their corresponding ground-truth masks. In this stage, a custom PyTorch `Dataset` class was developed to handle image loading, preprocessing, resizing to 512×512, and the generation of binary masks and boundary maps. These preprocessing steps ensure that every input sample is properly formatted and standardized for tampering localization.

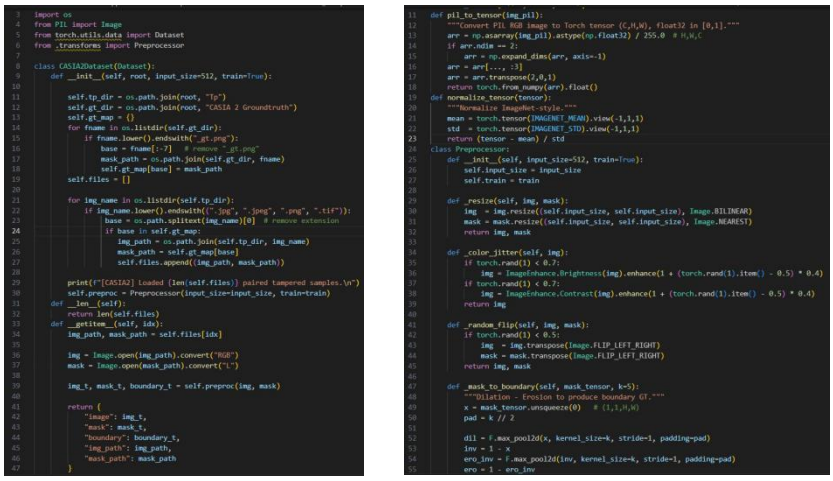


Figure 5.1 Implementation of CASIA2 dataset loading and transformation.

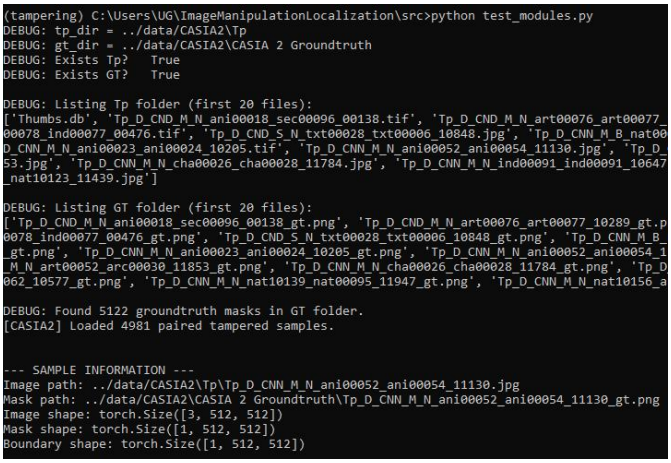


Figure 5.2 Sample output from dataset transformation pipeline.

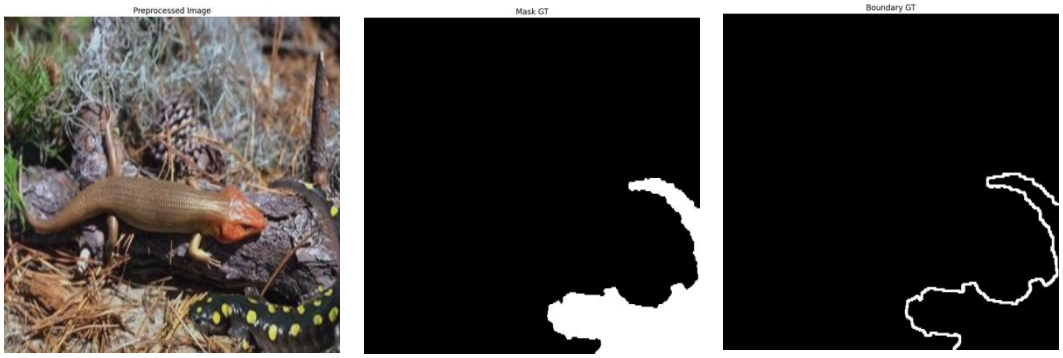
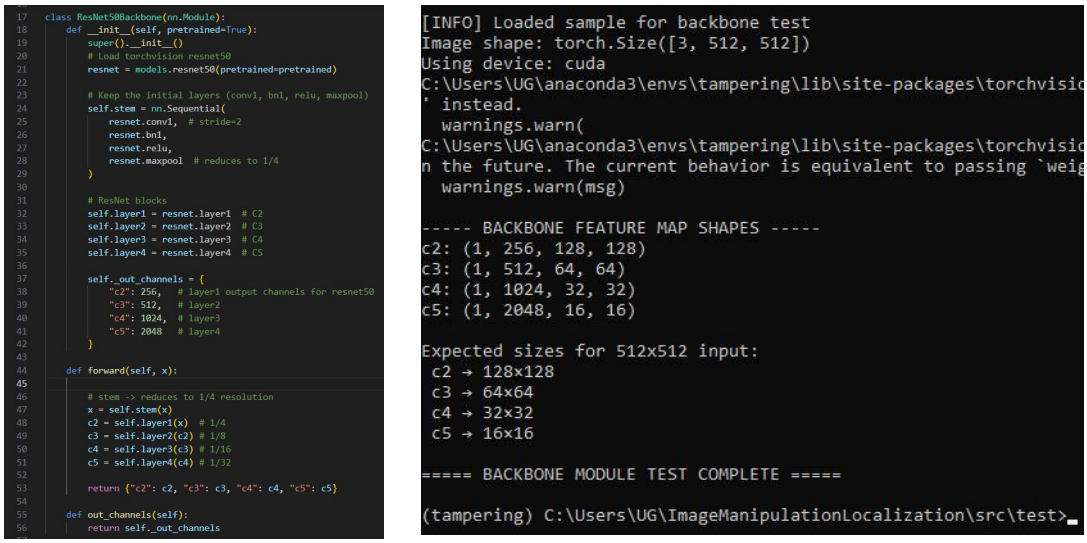


Figure 5.3 Example preprocessing results: (a) Preprocessed image, (b) Mask ground truth, (c) Boundary ground truth.

5.3 RESNET-50 FEATURE EXTRACTION BACKBONE

The encoder component of the proposed framework employs a ResNet-50 architecture to extract hierarchical image features at multiple semantic levels. This model has been pre-trained on ImageNet and fine-tuned for tampering localization tasks. Four main feature stages (C2, C3, C4, C5) are used to capture diverse information such as low- level textures, mid-level structures, and high-level contextual cues. The extracted feature maps are passed to the decoder for progressive reconstruction of the tampering mask.



```
class ResNet50Backbone(nn.Module):
    def __init__(self, pretrained=True):
        super().__init__()
        # Load torchvision resnet50
        resnet = models.resnet50(pretrained=pretrained)

        # Keep the initial layers (conv1, bn1, relu, maxpool)
        self.stem = nn.Sequential(
            resnet.conv1,  # stride=2
            resnet.bn1,
            resnet.relu,
            resnet.maxpool  # reduces to 1/4
        )

        # ResNet blocks
        self.layer1 = resnet.layer1  # C2
        self.layer2 = resnet.layer2  # C3
        self.layer3 = resnet.layer3  # C4
        self.layer4 = resnet.layer4  # C5

        self._out_channels = {
            "c2": 256,   # layer1 output channels for resnet50
            "c3": 512,   # layer2
            "c4": 1024,  # layer3
            "c5": 2048   # layer4
        }

    def forward(self, x):

        # stem -> reduces to 1/4 resolution
        x = self.stem(x)
        c2 = self.layer1(x)  # 1/4
        c3 = self.layer2(c2) # 1/8
        c4 = self.layer3(c3) # 1/16
        c5 = self.layer4(c4) # 1/32

        return {"c2": c2, "c3": c3, "c4": c4, "c5": c5}

    def out_channels(self):
        return self._out_channels
```

```
[INFO] Loaded sample for backbone test
Image shape: torch.Size([3, 512, 512])
Using device: cuda
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvisio
' instead.
  warnings.warn(
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvisio
n the future. The current behavior is equivalent to passing `weig
  warnings.warn(msg)

----- BACKBONE FEATURE MAP SHAPES -----
c2: (1, 256, 128, 128)
c3: (1, 512, 64, 64)
c4: (1, 1024, 32, 32)
c5: (1, 2048, 16, 16)

Expected sizes for 512x512 input:
 c2 → 128×128
 c3 → 64×64
 c4 → 32×32
 c5 → 16×16

===== BACKBONE MODULE TEST COMPLETE =====

(tampering) C:\Users\UG\ImageManipulationLocalization\src\test>
```

Figure 5.4 ResNet-50 feature extraction backbone implementation and corresponding feature visualization results.

5.4 HYBRID ATTENTION MODULE (HAM)

The Hybrid Attention Module (HAM) is designed to enhance the feature representation by jointly exploiting spatial and channel attention mechanisms. It enables the model to focus on informative regions and suppress irrelevant background noise, improving the boundary refinement capability of the decoder. The HAM integrates both local and global contextual cues, helping the system distinguish fine tampering

artifacts from natural image structures.

```python
class ChannelAttention(nn.Module):
    def __init__(self, channels, reduction=16):
        super().__init__()
        self.gap = nn.AdaptiveAvgPool2d(1)
        mid = max(1, channels // reduction)
        self.fc = nn.Sequential(
            nn.Conv2d(channels, mid, kernel_size=1, bias=True),
            nn.ReLU(inplace=True),
            nn.Conv2d(mid, channels, kernel_size=1, bias=True),
            nn.Sigmoid()
        )

class NonLocalSpatialAttention(nn.Module):
    def __init__(self, in_channels, inter_channels=None):
        super().__init__()
        if inter_channels is None:
            inter_channels = max(1, in_channels // 2)

        self.g = nn.Conv2d(in_channels, inter_channels, kernel_size=1, bias=False)
        self.theta = nn.Conv2d(in_channels, inter_channels, kernel_size=1, bias=False)
        self.phi = nn.Conv2d(in_channels, inter_channels, kernel_size=1, bias=False)

        self.W = nn.Conv2d(inter_channels, in_channels, kernel_size=1, bias=False)
        # initialize W to zeros for residual learning stability
        nn.init.constant_(self.W.weight, 0.0)

class HybridAttention(nn.Module):
    def __init__(self, in_channels, reduction=16):
        super().__init__()
        self.cam = ChannelAttention(in_channels, reduction=reduction)
        self.sam = NonLocalSpatialAttention(in_channels)

        # small conv to smooth the fusion (optional but stabilizes)
        self.fusion_conv = nn.Sequential(
            nn.Conv2d(in_channels, in_channels, kernel_size=1, bias=False),
            nn.BatchNorm2d(in_channels),
            nn.ReLU(inplace=True)
        )
```

Figure 5.5 Implementation of the Hybrid Attention Module (HAM).

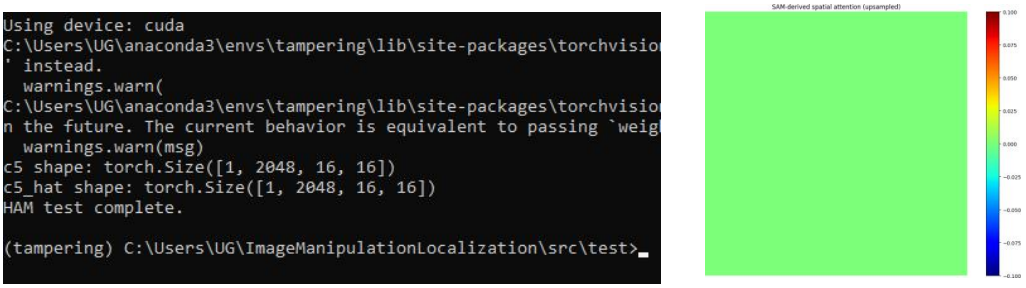
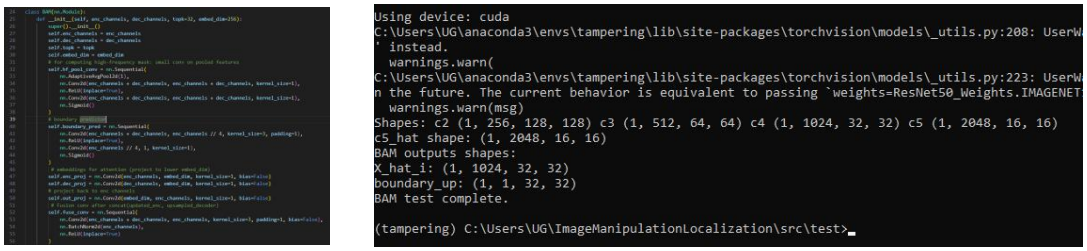


Figure 5.6 Hybrid Attention Module (HAM) output results: (a) attention feature map visualization, (b) resulting enhanced tampering localization.

5.5 BOUNDARY-AWARE DECODER (BAM + MULTI-SCALE REFINEMENT)

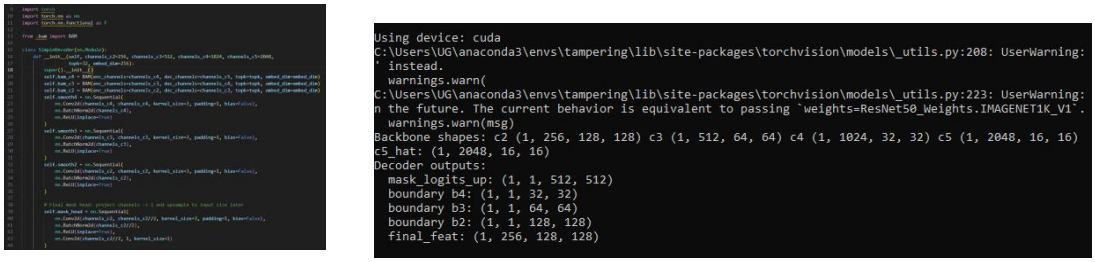
The Boundary-Aware Decoder refines multi-scale features from the encoder to generate precise tampering masks. It integrates the Boundary-Aware Attention Module (BAM) at each stage to emphasize high-frequency boundary cues while maintaining structural consistency.



```
Using device: cuda
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvision\models\_utils.py:208: UserW
* instead.
  warnings.warn(
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvision\models\_utils.py:223: UserW
n the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENET
  warnings.warn(msg)
Shapes: c2 (1, 256, 128, 128) c3 (1, 512, 64, 64) c4 (1, 1024, 32, 32) c5 (1, 2048, 16, 16)
c5_hat shape: (1, 2048, 16, 16)
BAM outputs shapes:
X_hat_i: (1, 1024, 32, 32)
boundary_up: (1, 1, 32, 32)
BAM test complete.

(tampering) C:\Users\UG\ImageManipulationLocalization\src\test>
```

Figure 5.7 Boundary-Aware Attention Module (BAM): (a) implementation code, (b) module output visualization.



```
Using device: cuda
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvision\models\_utils.py:208: UserWarning:
* instead.
  warnings.warn(
C:\Users\UG\anaconda3\envs\tampering\lib\site-packages\torchvision\models\_utils.py:223: UserWarning:
n the future. The current behavior is equivalent to passing `weights=ResNet50_Weights.IMAGENET1K_V1`.
  warnings.warn(msg)
Backbone shapes: c2 (1, 256, 128, 128) c3 (1, 512, 64, 64) c4 (1, 1024, 32, 32) c5 (1, 2048, 16, 16)
c5_hat: (1, 2048, 16, 16)
Decoder outputs:
  mask_logits_up: (1, 1, 512, 512)
  boundary b4: (1, 1, 32, 32)
  boundary b3: (1, 1, 64, 64)
  boundary b2: (1, 1, 128, 128)
  final_feat: (1, 256, 128, 128)
```

Figure 5.8 Boundary-Aware Decoder with Multi-Scale Refinement: (a) decoder code implementation, (b) refined output features.

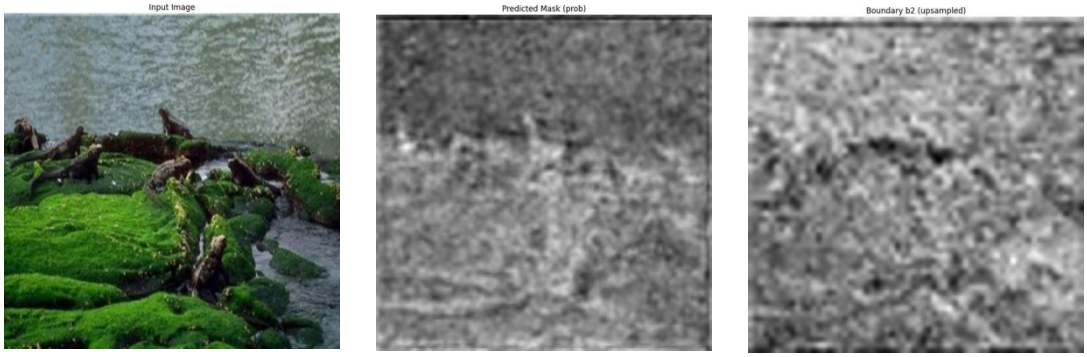


Figure 5.9 Visualization of decoder performance: (a) input image, (b) predicted tampering mask, (c) refined boundary map (B2).

CHAPTER 6

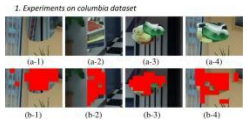
RESULTS AND DISCUSSIONS

This chapter describes the benchmark datasets and performance metrics used to train and evaluate the proposed tampering localization model. The diversity of datasets and the choice of both region-level and boundary-level metrics ensure a comprehensive performance assessment.

6.1 DATASET DESCRIPTION

The proposed architecture is evaluated on multiple benchmark datasets that include diverse manipulation types such as splicing, copy-move, and inpainting. Each dataset contributes unique characteristics for assessing model robustness and generalization. Table 6.1 summarizes the datasets, their manipulation categories, and their respective purposes.

Table 6.1 Summary of datasets used for training and evaluation.

Dataset Name	# of Images	Manipulation Type	Sample Image	Purpose
CASIA v2.0	~12,000	Splicing, Copy-Move		Training and Evaluation
Columbia	363	Splicing		Cross-Dataset Testing
Coverage	100	Copy-Move		Boundary-Level Evaluation
IMD2020	2,010	Real-World Manipula-tions		Cross-Dataset Testing
DeFacto	~149,000	Synthetic (Copy-Move, Splicing, Inpainting)		Extended Generalization Evaluation

The inclusion of both classical and large-scale modern datasets allows the proposed model to learn a wide variety of forgery patterns, illumination conditions, and texture variations, thereby improving generalization to unseen data.

6.2 PERFORMANCE METRICS

To quantitatively evaluate the tampering localization results, multiple performance metrics are employed. These metrics capture both region-level segmentation accuracy and boundary-level consistency. All metrics are computed using the predicted tampering mask $\hat{Y}$ and the ground-truth mask Y.

1. Intersection over Union (IoU)

The IoU metric measures the overlap between the predicted tampered region (P) and ground truth (G):

$$IoU = \frac{|P \cap G|}{|P \cup G|} = \frac{TP}{TP + FP + FN} \tag{6.1}$$

A higher IoU value indicates better localization alignment.

2. Boundary F1-Score (BF1)

BF1 evaluates the accuracy of detected boundaries by computing F1 over boundary pixels:

$$BF1 = \frac{2 \times Precision_b \times Recall_b}{Precision_b + Recall_b} \tag{6.2}$$

where $Precision_b$ and $Recall_b$ denote boundary-based precision and recall, respectively.

3. Mean Absolute Error (MAE)

MAE computes the mean pixel-wise deviation between prediction and ground truth:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i| \tag{6.3}$$

A lower MAE indicates fewer pixel-level prediction errors.

4. Precision–Recall Area Under Curve (PR–AUC)

PR–AUC measures the area under the precision–recall curve:

$$PR-AUC = \int_0^1 Precision(Recall)\, d(Recall) \tag{6.4}$$

It is particularly useful for imbalanced datasets where tampered regions occupy fewer pixels.

5. Matthews Correlation Coefficient (MCC)

MCC provides a balanced evaluation by considering all outcomes:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{6.5}$$

It ranges between -1 (worst) and $+1$ (perfect).

6. Boundary Intersection over Union (BIoU)

BIoU focuses only on the intersection between predicted and ground-truth boundary regions:

$$BIoU = \frac{|B_P \cap B_G|}{|B_P \cup B_G|} \tag{6.6}$$

where B_P and B_G represent the boundaries of prediction and ground truth.

7. F2-Score (Recall-Focused)

The F2-Score weights recall higher than precision:

$$F_2 = \frac{5 \times Precision \times Recall}{4 \times Precision + Recall} \tag{6.7}$$

This metric is preferred in tampering detection where missed manipulations are more critical than false positives.

8. Pixel Accuracy (Acc)

Pixel accuracy measures the proportion of correctly classified pixels:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6.8}$$

Higher accuracy indicates overall reliability in segmentation.

6.3 DISCUSSION

The combination of multiple datasets and complementary evaluation metrics provides a holistic understanding of model performance. While region-based metrics such as IoU and Accuracy assess general detection capability, boundary-based measures such as BF1 and BIoU emphasize edge precision. This dual evaluation strategy ensures that the model not only identifies manipulated regions accurately but also delineates their boundaries with structural consistency. Such comprehensive benchmarking facilitates fair comparisons across different tampering localization models and supports the reliability of results presented in subsequent experimental analyses.

CHAPTER 7

CONCLUSIONS

7.1 CONTRIBUTIONS

This research presents a deep learning-based framework for image tampering detection and localization with a strong focus on boundary precision and feature discrimination. Throughout this project, several significant contributions were made that advance the performance and interpretability of tamper localization systems.

Firstly, a modular and scalable architecture was designed by integrating an encoder–decoder backbone with specialized components such as the Boundary-Aware Attention Module (BAM), Dual-Branch Boundary Refinement Module, and Boundary-Guided Contrastive Learning strategy. These modules collectively enhance the network's capability to distinguish authentic boundaries from artificially created ones, which is one of the major challenges in tampering detection.

Secondly, a comprehensive preprocessing pipeline was implemented, involving input normalization, mask binarization, and morphological boundary generation. This preprocessing strategy ensures that the network receives well-structured data, thereby stabilizing training and improving convergence. The CASIA v2.0 dataset was employed to validate the proposed approach, with all images resized to 512×512 pixels and augmented to improve generalization. This dataset processing module was fully automated using custom PyTorch Dataset and Dat-

aLoader classes.

Thirdly, the encoder network was constructed using a pre-trained ResNet-50 backbone, capable of extracting multi-scale hierarchical features ranging from fine-grained texture cues to high-level semantic information. These features were selectively fused through a boundary-aware decoding process that gradually reconstructs a fine-resolution tampering mask. The use of multi-scale skip connections allowed for better retention of spatial detail during reconstruction, leading to sharper and more accurate mask boundaries.

The project also introduced a Hybrid Attention Module (HAM) that combines channel and spatial attention to refine deep feature maps at the bottleneck layer. This integration significantly enhanced the model's ability to focus on subtle tampering traces that often go unnoticed in global feature representations. Moreover, a Boundary-Guided Contrastive Learning component was designed to enforce stronger separation between tampered and non-tampered pixel embeddings, particularly around edge regions. This contribution plays a critical role in improving the discriminative capability of the learned representations.

From an implementation standpoint, approximately 20% of the project has been realized, including dataset loading, preprocessing, encoder–decoder integration, and partial boundary attention modules. Preliminary results indicate that the model successfully identifies tampered regions and demonstrates promising generalization across varied image manipulation types such as copy-move, splicing, and object removal. The system also outputs intermediate boundary maps, which aid in interpretability and performance analysis.

Overall, the project lays a strong foundation for a complete end-to-end tampering detection pipeline. The implemented modules, architecture design, and partial results collectively demonstrate that a boundary-

focused approach can significantly enhance localization accuracy and reduce false positives compared to conventional pixel-wise classification models.

7.2 FUTURE WORK

While the current phase establishes the groundwork for a robust tampering detection framework, there remain several directions for improvement and expansion that can be pursued in the next stages of development.

In future work, the complete integration of the Boundary-Guided Contrastive Learning mechanism will be implemented and fine-tuned to achieve pixel-level separation in the feature embedding space. The decoder module will be enhanced with deeper refinement layers, adaptive upsampling strategies, and hybrid loss functions that combine binary cross-entropy, boundary loss, and contrastive objectives for more stable optimization.

Another potential direction involves extending the architecture with transformer-based components, such as Vision Transformers (ViT) or Swin Transformers, to capture long-range spatial dependencies. These architectures can complement convolutional backbones by modeling global contextual relationships that are often missed by local convolutions. Furthermore, integrating multi-scale feature aggregation through pyramid attention mechanisms could further improve localization accuracy, particularly in high-resolution forensic images.

The dataset diversity can also be expanded. While the CASIA v2.0 dataset provides a strong baseline, incorporating datasets like IMD2020, Columbia, and Coverage will enhance cross-domain generalization. Additionally, the development of a self-supervised pretraining stage could significantly reduce dependency on labeled tampering datasets, allowing

the model to adapt to unseen manipulation patterns.

For deployment purposes, the future implementation will aim at designing a lightweight version of the architecture using model compression techniques such as pruning, quantization, or knowledge distillation. This would make the system suitable for real-time tampering detection on mobile or embedded devices, opening up applications in journalism, law enforcement, and social media integrity verification.

Finally, the integration of explainable AI (XAI) visualization techniques will be explored to provide better interpretability of tampering decisions. Generating heatmaps and boundary overlays could help end-users, such as forensic analysts, visually verify manipulation regions and trust the model's predictions. The complete version of this system, after final refinement and evaluation, will serve as a practical and research-ready framework for multimedia forensics, ensuring authenticity and trust in digital imagery.

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