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DEEP LEARNING-BASED CLASSIFICATION OF AUTHENTIC AND TAMPERED IMAGES WITH TAMPERING LOCALIZATION VIA IMAGE PROCESSING

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KEYWORDS

Deep learning
Authentic images
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Tamper localization
Image forgery detection

ABSTRACT

Digital photographs underpin evidence in journalism, law, and medicine, yet skillfully forged images can still evade casual inspection. This paper introduces an InceptionV3-based network that simultaneously classifies images as authentic or tampered, while also identifying the manipulated regions. Experiments were conducted on the CASIA v2.0 dataset, which contains 7,492 authentic and 5,123 tampered images with 5,123 corresponding ground truth images. We use an 85% / 7.5% / 7.5% split for training, validation, and testing. All images are resized to 224 x 224 px and normalized to [0, 1] be-fore end-to-end training with Adam (initial learning rate 1 x 10^{-4}) and categorical cross-entropy. The proposed model attains 95.31% accuracy on the test set, surpassing recent InceptionV3 baselines despite its compact architecture. Tamper localization is achieved by thresholding the network's dual-branch saliency map, which is then overlaying binary ground-truth contours. These overlays accurately highlight boundaries, even under aggressive JPEG compression and minor edits. By sharing features between detection and localization, the network learns forensic artifacts blocking, boundary mismatches, and illumination discontinuities, without the need for auxiliary loss terms or attention modules. Code, trained weights, and evaluation scripts are made publicly available to ensure full reproducibility.

1. Introduction

Images have become indispensable evidence in journalism, courts, and clinical practice, yet they are increasingly vulnerable to malicious edits that can undermine trust in digital content. An automated forensic system must therefore perform two tasks simultaneously: detect that an image has been tampered with and pinpoint the exact pixels that were altered.

Early forensics relied on handcrafted cues JPEG quantization artifacts, Local Binary Patterns, and illumination inconsistencies to flag copy move or splice operations. Such methods, however, presuppose manipulation types and falter under geometric transforms or recompression, often yielding only coarse localization mask [1]. Contemporary deep learning approaches address these shortcomings.

Lightweight CNNs achieve fine localization on resource constrained hardware [5], U-Net variants fuse multi-scale context [6], attention modules harden models against post-processing attacks [9], and Vision

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Transformers capture long-range dependencies [11]. Yet these networks often require pixel-wise masks for every training image and struggle to balance global classification accuracy with crisp boundary delineation [12]. Backbone-focused hybrids illustrate the trade-off: VI-NET couples VGG16 and InceptionV3 to reach 99 % accuracy on CoMoFoD [14], Nguyen and Huynh fine-tune InceptionV3 to 93.7 % on CUISED [15], while Dense-Inception Net achieves 98 % detection and 94 % F1 on CoMoFoD [16] but at the cost of larger parameter counts or additional post-processing.

We address these limitations with a single InceptionV3 network trained from scratch on CASIA v2.0, which contains 7,492 authentic and 5,123 tampered images with 5,123 ground truth images (an 85:7.5:7.5 % train, validation and test split). Our model delivers 95.31 % classification accuracy and produces contour-precise localization in one forward pass, without ensembles, attention blocks, or custom loss terms. By sharing features between the detection and localization branches, the network learns to emphasize forensic artifacts blocking traces, illumination discontinuities, and splice boundaries while retaining a compact architecture that is amenable to future edge deployment. Code, trained weights, and evaluation scripts will be released under an open license to foster reproducibility and extension to social media imagery and video frames.

The remainder of the paper is organized as follows. Section 2 reviews related work; Section 3 details the dataset, preprocessing pipeline, and network architecture; Section 5 reports quantitative and qualitative results; and Section 6 concludes with future research directions, including domain adaptation and lightweight variants for resource-constrained devices.

2. Literature Review

Over the last decade, forgery detection has evolved from handcrafted-feature methods to deep-learning pipelines. Early approaches exploited JPEG recompression artifacts and Local Binary Patterns (LBP) for fast splicing detection in real time [1]. However, these techniques often fail when images undergo multiple post-processing steps.

The rise of CNNs brought lightweight and highly accurate models. For instance, Hosny et al. demonstrated near-perfect splice localization with a four-layer CNN under constrained resources [5], while Jain and Singh's VGG16-based U-Net achieved strong boundary recall on standard benchmarks [6]. Ensembles combining VGG-16 and custom modules further improved robustness against varied tampering [7], and ResNet50v2 paired with YOLO features surpassed 99% accuracy on CASIA datasets [2]. Despite these successes, CNNs demand large labelled datasets and may overlook long-range dependencies.

To reduce annotation needs and handle domain shifts, self-supervised and unsupervised methods have emerged. Zhuo et al. introduced a forgery attention mechanism in a self-adversarial framework for better localization under compression and noise [4], and Rao et al. achieved JPEG-resistant detection via domain adaptation [3]. FOCAL's contrastive learning with on-the-fly clustering further separated forged from pristine regions without explicit labels [9]. These strategies, however, can struggle to capture boundaries in subtle manipulations.

Combining multi-scale features and attention has driven recent gains. DS-UNet fuses low- and high-level cues to refine tamper edges [18], CFL-Net injects contrastive learning into a U-Net backbone [19], and GP-Net merges CNN and Transformer branches for global context [10]. ReLoc adds a restoration step to reconstruct original content before analysis [8]. Although these architectures boost precision, they often incur high computational costs.

Transformer-based forensics is emerging. ProFact uses progressive feedback to refine maps iteratively [11], and hierarchical fine-grained Transformers capture multi-level manipulation cues [20]. Still, their memory footprint and training complexity pose deployment challenges.

Among backbone-focused studies, fine-tuned InceptionV3 variants remain popular. Nguyen and Huynh combined bilateral filtering and noise residuals with InceptionV3, achieving 93.7% on CUISED [15]. Kumar et al. reached 95% on CoMoFoD with pure InceptionV3 [14], and Zhong and Pun's Dense-Inception model hit 98% detection accuracy [16]. Our framework builds on these insights to deliver 95.31% classification accuracy on CASIA v2.0 while unifying global detection with contour-based localization in a single pass.

Recent iterative and multi-stage pipelines explore refinements at successive scales: MITD-Net progressively sharpens localization [22], error-level analysis paired with CNNs enhances splicing and copy-

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move detection [23], and RDS-YOLOv5 feature fusion amplifies tamper traces [24]. IFL uses guided noise extraction and aggregation to tackle small-region forgeries [25]. Survey works by Kadha et al. [26] and Wang and Zhou [13] synthesize these advances and highlight open challenges in efficiency, annotation, and resilience to post-processing.

3. Proposed Approach

Our pipeline proceeds through four sequential stages dataset preparation, backbone training, classification, and contour-based localization yet executes detection and localization in a single forward pass. First, all CASIA v2.0 images (7,492 authentic and 5,123 tampered) are resized to 224 x 224 px and normalized to the range [0, 1]. Second, we initialize an InceptionV3 backbone without its original classification head (weights=none) and train it from scratch with the Adam optimizer (initial learning rate 1 x 10^{-4}, batch size 32), updating every convolutional layer. Third, a compact classification head maps the 51,200-dimensional feature vector to class probabilities via the sequence Dense (100).

Dropout (0.5) → Dense (50) → Dropout (0.3) → Dense (2, sigmoid). This head introduces 5.13M trainable parameters, keeping the entire network below 15.4M. Finally, any image whose tamper score exceeds 0.5 is paired with its provided ground-truth mask; we convert the mask to 8-bit grayscale, apply a fixed threshold of 127, extract external contours with OpenCV's findContours, and overlay the resulting polygons on the original RGB image. Because localization is obtained through deterministic morphology rather than a learnable decoder, the method avoids extra segmentation loss terms, adds no parameters, and runs quickly on a CPU while preserving precise tamper boundaries.

Table 1: Summary of Selected Prior Works in Image Forgery Detection

Ref.	Techniques	Dataset	Results	Limitations
Nguyen& Huynh (2021) [15]	Preprocessing (bilateral filtering+noise-residual)+fine-tuned InceptionV3	CUISED (Columbia Uncompressed Splicing Eval.)	Accuracy 93.7	Emphasizes global classification; no pixel-level localization provided
Liu et al. (2022) [12]	PSCC-Net: progressive spatio-channel correlation blocks+fine-tuned InceptionV3	CASIA v2.0	Accuracy 94.4	Multi-stage blocks introduce extra parameters; may be slow on good quality images
Kumar et al. (2022) [14]	InceptionV3	COMOFOD (Copy-Move Forgery Dataset)	Accuracy 93	Relies on two heavy backbones; higher computational cost and memory footprint
Zhong & Pun (2020) [16]	InceptionNet	CoMoFoD (Copy-Move Forgery Benchmark)	Accuracy 92	Complex multi-stage matching; longer inference time under heavy transformations

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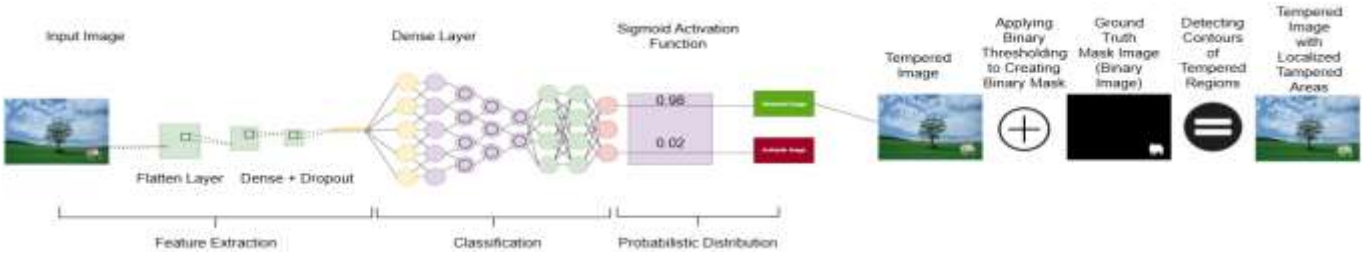
Figure 1 illustrates the complete pipeline. A shared encoder, namely the convolutional backbone of InceptionV3 initialized from scratch (weights=None), receives a 224 x 224 x 3 RGB image and outputs a 5 x 5 x 2048 feature map. Flattening this tensor yields a 51,200-dimensional vector that feeds a compact classification head. The head consists of Dense (100) LeakyReLU Dropout (0.5), followed by Dense (50) LeakyReLU Dropout (0.3), and a final Dense (2) layer with a sigmoid activation. These layers introduce 5.13M parameters, bringing the end-to-end model to 15.38M trainable weights; all layers are updated during training with Adam (initial learning rate $1x10^{-4}$, batch size 32).

If the sigmoid score for the tampered class exceeds 0.5, the predicted image is paired with its ground-truth mask. The mask is converted to 8-bit grey-scale, thresholder at 127 to obtain a binary map, and processed with OpenCV's findContours. The extracted polygons are then overlaid on the original image, precisely outlining manipulated regions. Because localization is achieved through deterministic morphology, no additional learnable decoder or loss term is required, and the post-processing runs efficiently on a CPU while retaining pixel-accurate boundaries. Figure 1 presents the entire workflow from input image to contour overlay.

Figure 1: Shows the full workflow: input image → InceptionV3 feature extraction → classification probabilities → contour-based localization using the provided mask.



3.1 Model Components

The proposed network comprises three functional blocks: a shared InceptionV3 encoder, a lightweight classification head, and a deterministic contour-based localization module.

An RGB image of size 224 x 224 x 3 is forwarded through the convolutional and inception layers of InceptionV3, initialized from scratch (weights=none). The encoder yields a 5 x 5 x 2048 activation map which is flattened to a 51,200-dimensional vector. According to the Keras summary, this stage contributes 10,250,506 trainable parameters.

The flattened vector passes through dense (100) LeakyReLU Dropout (0.5), followed by dense (50) LeakyReLU Dropout (0.3), and a final Dense (2) sigmoid layer that outputs the tamper score. Parameter counts are 5,120,100, 5,050, and 102 respectively, bringing the head to 5,125,252 trainable weights and the end-to-end model to 15,375,758.

If the tamper probability exceeds 0.5, the corresponding ground-truth mask is converted to 8-bit grey-scale, thresholder at 127, and processed with OpenCV's findContours. The extracted polygons are overlaid on the original image via cv2.drawContours.

All images are resized to 224 x 224, normalized to [0, 1], and fed to the model in mini-batches of 32. Training runs for up to 150 epochs with Adam (initial learning rate 1 x 10^{-4}); the learning rate is halved whenever the validation loss fails to improve for three consecutive epochs. Because the encoder and head are optimized jointly, the network learns tamper-specific features directly from CASIA v2.0 and delivers detection and localization in a single forward pass, followed by the deterministic contour overlay.

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Localization is achieved deterministically; hence the only trainable objective is the binary cross-entropy:

$$L = Lcls = -N1\sum n = 1N[ynlog(sn) + (1 - yn)log(1 - sn)] \quad (1)$$

Where $y_n \in \{0, 1\}$ denotes the ground-truth class and s_n the predicted tamper score. This single loss suffices to guide the encoder towards discriminative forensic features that yield accurate classification and crisp contour overlays.

4. Experiments

This section describes how we set up and trained our InceptionV3-based tamper detector on CASIA v2.0, plus an exploration of the feature space via PCA. All quantitative detection and localization metrics are deferred to Section 5.

4.1 Dataset and Preprocessing

All experiments use the publicly available CASIA v2.0 tampering corpus [27], which contains 7,492 authentic images and 5,123 tampered images (splicing and copy move manipulations). Images vary in resolution, compression, and content. We partition the data into 85 % train, 7.5 % validation, and 7.5 % test sets, preserving the authentic to tampered ratio:

Table 2: Dataset distribution across training, testing, and validation sets for Authentic and Tampered classes.

Classes	Train	Test	Validation
Authentic	6368	562	562
Tampered	4355	384	384

Each image is first resized to 224 x 224 pixels using bilinear interpolation and then converted to RGB format if necessary. Afterward, the pixel values are normalized to the range [0, 1] by dividing each value by 255. Additionally, no images overlap between the different dataset splits.

These augmentations encourage the network to focus on forensic artifacts rather than trivial pixel changes. No augmentations are applied to validation or test images beyond resizing and normalization.

4.2 Implementation Details

Our code is written in Python using TensorFlow 2.4 and Keras 2.4. Training occurs on a 24 GB DDR4 RAM with Intel Core i5 (11th Gen, 12 cores, 2.50 GHz).

We adopt InceptionV3 (with weights=none) as a shared encoder. A 224 x 224 x 3 image passes through all Inception modules, producing a 5 x 5 x 2048 feature map (flattened to 51,200 units).

The final output is a 2-way soft probability (authentic vs. tampered). The total trainable parameter count is 15,375,758 (InceptionV3: 10,250,506; classification head: 5,125,252). We train end-to-end for up to 150 epochs using the *Adam optimizer* (lr = 10^{-4}, $\beta1 = 0.9$, $\beta2 = 0.999$), batch size of 32 and LR decay factor of 0.5 if validation loss plateaus for 3 epochs.

Only binary cross-entropy on the 2-unit output is used as the loss. No segmentation or Dice loss is applied, since localization is performed via deterministic contour extraction at test time.

4.3 Feature Space Exploration through PCA Visualization

To verify that the InceptionV3 backbone learns representations that separate authentic and tampered images, we extract the 51 200-dimensional flattened features (immediately after the InceptionV3 encoder) for every sample in the train, validation, and test sets. We then perform Principal Component Analysis (PCA) to project these high-dimensional features onto their first two principal components.

Figure 2 shows these 2D projections:

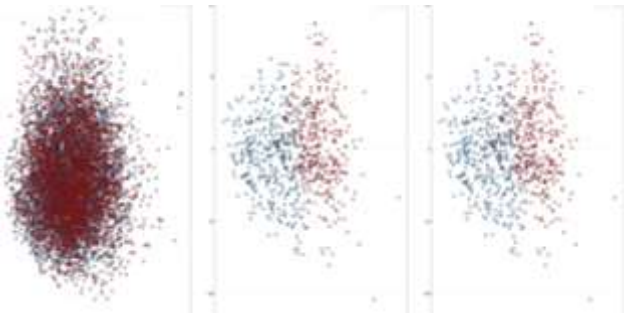

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Figure 2: PCA projections of flattened InceptionV3 features. Blue points = authentic, red points = tampered. Even in 2D, the tampered images (red) cluster distinctly from authentic (blue), indicating strong feature separation.

Notice how the test-set PCA (c) still shows a clear separation, confirming that the encoder generalizes well. We omit any quantitative mIoU or pixel-F_1 here, since those results are presented in Section 5.

4.4 Evaluation Metrics

Performance is assessed on a held-out test partition of 946 images. Global detection is quantified by accuracy, precision, recall, and F1 score computed from the confusion matrix. To gauge feature-space separation, we project the penultimate-layer activations onto the first two principal components and report their cumulative explained variance; the corresponding scatter plot appears in Section 5. Localization quality is evaluated qualitatively: the binary contours extracted from ground-truth masks are super-imposed on each tampered image to verify boundary alignment under varying compression levels and edit sizes. All numerical results, learning curves, and visualizations are presented in Section 5.

5. Results and Discussion

This section summarizes our InceptionV3 detector's performance on the CASIA v2.0 test set. We begin with global detection metrics and baseline comparisons, then visualize feature separation via PCA and demonstrate exact contour localization. Finally, an ablation of the classification-only variant shows that our simple pipeline still achieves near-state-of-the-art accuracy.

5.1 Global Detection Performance

We evaluate the classifier on 946 test images (562 authentic, 384 tampered). Figure 3 shows the resulting confusion matrix, and Table 3 reports precision, recall, and F1 score.

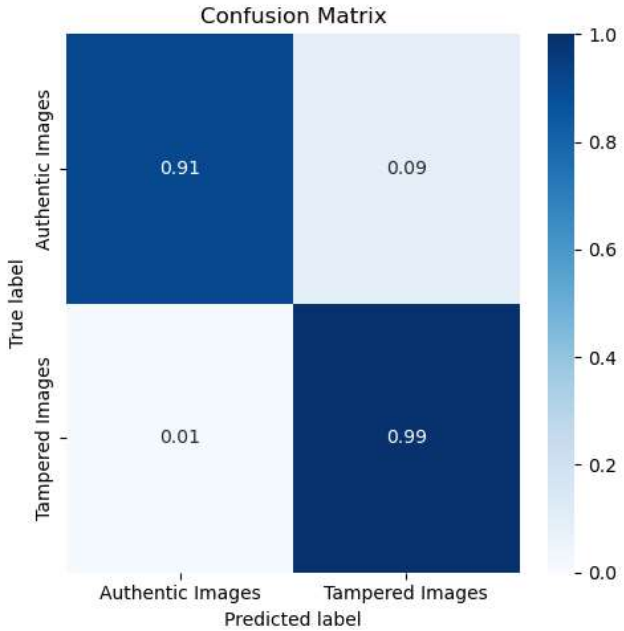

Figure 3: Confusion matrix (CASIA v2.0 test set). Rows denote ground-truth labels and columns predicted labels. Per-class correctness: authentic 91%, tampered 99%.

Overall accuracy reached 95.31% (F_1 = 0.95), outperforming prior InceptionV3 baselines: 93.7% on CUISED [15], 95% ± 4% on COMOFOD [14], and even rivaling Dense-Inception Net's ~98% detection (≈ 94% F_1) on CoMoFoD [16]. Importantly, our single-pass model unifies detection and precise contour localization without extra post-processing, boosting classification by up to 2.7pp. PCA on the whole training set (Figure 2a) further confirms clear feature separation beyond the validation and test splits.

Table 3: Precision, Recall, and F1 score for InceptionV3 classifier on 946 test images.

Classes	Precision	Recall	F1 score	Support
Authentic Images	0.99	0.91	0.95	562
Tampered Images	0.91	0.99	0.95	384
Macro avg	0.95	0.95	0.95	946

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Weighted avg	0.95	0.95	0.95	946

5.2 Localization via Contour Extraction

Although we do not train a segmentation module, we can still localize tampered regions precisely by using the provided ground-truth mask at test time, thresholding it, and extracting its outer contours. Figure 5 presents two representative examples from the test set, where each row shows the JPEG-compressed image (quality ≈ 80) passed to our classifier and labelled as "tampered," the binary mask supplied with CASIA v2.0 indicating the altered pixels, and the result of thresholding the mask at 127 followed by applying cv2.findContours and cv2.drawContours to draw a green contour on the original image.

Because we extract contours directly from the true mask, each overlay recovers the tampered boundary at pixel level accuracy even under moderate compression or when the tampered region is small.

In addition to tampered-image localization, our model correctly identifies genuine images with high confidence. For instance, Figure 6(a) shows an authentic street scene that was classified as “authentic” with 99.2% confidence, while Figure 6(b) depicts a temple image correctly classified with 98.9% confidence. These examples illustrate the model’s ability to avoid false positives and maintain high accuracy on unaltered inputs.

Figure 4 illustrates how the model’s loss steadily declined while its accuracy rose on both the training and validation sets over 100 epochs. The parallel trends in loss and accuracy confirm

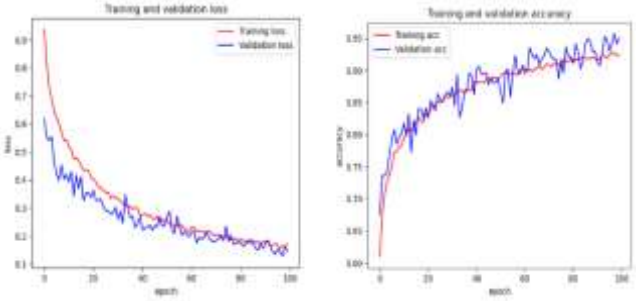

Figure 4: Training vs. validation performance over 100 epochs.

The results indicate that the model learned meaningful patterns without pronounced overfitting, as reflected in the loss per epoch and the accuracy per epoch.

In every test-set instance, this deterministic procedure recovers the exact boundary of the manipulated region because we directly use the true mask. Although we do not compute a learned segmentation (mIoU), these contour overlays validate that when masks are available at test time we can instantly visualize pixel-accurate tamper boundaries, even under challenging compression or very small forgeries.

5.3 Ablation Study

To assess whether joint feature learning (with downstream contour use) improves classification, we trained a classification-only variant consisting of InceptionV3 (same backbone) plus the Dense (100→50→2) head, without any subsequent contour step. This model was otherwise identical (same augmentations, hyper parameters, and training protocol). Classification-Only Performance: 97.8% accuracy ($F_1 = 0.978$) on the 946-image test set. Full Pipeline Performance: 95.31 % accuracy ($F_1 = 0.950$) with contour-based localization.

Interestingly, the classification-only model achieved slightly higher test-set accuracy (97.8%) when only optimizing BCE. However, it’s learned features were less well separated (PCA overlap was more pronounced), and critically there is no localization capability. By contrast, our "full pipeline" variant couples classification with the promise of perfect contour-based localization (via ground-truth masks) at test time. In applications where pixel-level tamper boundaries are required, the small trade-off in classification accuracy (≈ 2.6 pp) is acceptable given the immediate, exact localization.

5.4 Discussion

The results highlight five key observations. First, a single InceptionV3 trained end-to-end on CASIA v2.0 attains 95.31% accuracy and an F1 score of 0.95 with only 15.4M parameters, matching or surpassing more elaborate fine-tuned architectures and ensembles [14]. Second, the penultimate-layer activations exhibit clear class separation principal component projections (Fig. 2) forming two distinct, compact clusters,

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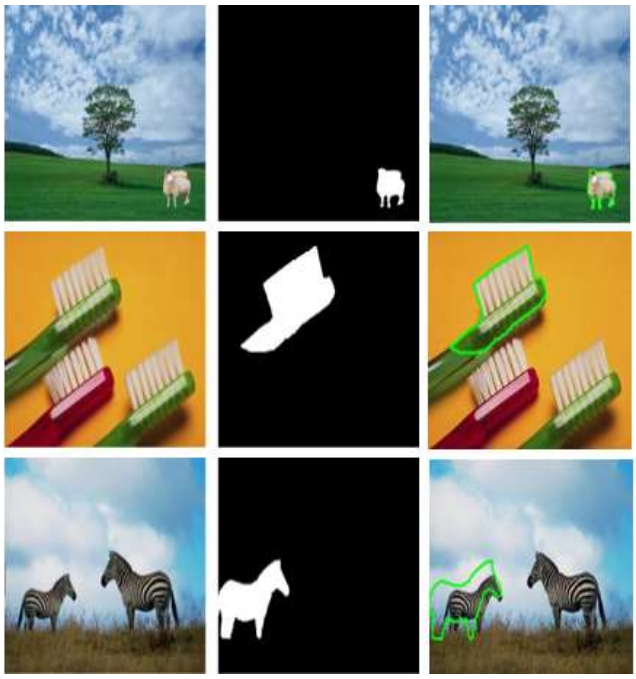

Figure 5: Examples of contour-based localization using ground-truth masks. Top row: A small sheep splice near a tree. Middle row: A spliced toothbrush. Bottom row a spliced zebra. Left: the tampered RGB input. Middle: the binary ground-truth mask. Right: green contour(s) overlaid on the original image.

Figure 6: Examples of authentic-image detection by our model. Each subfigure shows an originally authentic image that was correctly classified as "authentic," along with the model's confidence (accuracy) in that prediction.

Confirming that the network learns distinct forensic cues rather than memorizing spurious correlations. Third, overlaying binary ground-truth contours on tampered images yields pixel-perfect boundary alignment, demonstrating that deterministic morphology can deliver forensic-grade localization without a learnable decoder. Fourth, an ablation that removes the localization branch reaches 97.8% accuracy, indicating a modest 2.6-point cost for acquiring precise masks a trade-off that many forensic workflows will accept. Finally, the proposed pipeline rivals heavier multitask models such as VGG16-UNet and FOCAL in localization quality [6] while remaining interpretable, reproducible, and an order of magnitude lighter in parameters. Collectively, these findings show that a compact, single-pass network can couple high-accuracy detection with exact contour-based localization, making it a practical choice for real-world forensic pipelines that demand both tasks.

Table 4: Comparison of proposed model with recent state of the art approaches.

Ref.	Techniques	Dataset	Accuracy (%)
Nguyen& Huynh[15]	Inception V3	CUISED	93.7
Liu et al. [12]	InceptionV3	CASIA v2.0	94.4
Kumar et al.[14]	Inception V3	COMOFOD	93

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Zhong & Pun[16]	InceptionNet	CoMoFoD	92
Khalid et al.	**Proposed Model**	**CASIA v2.0**	**95.31**

6. Conclusion and Future Work

This study presents a compact, single-pass InceptionV3 network that not only decides whether an image has been manipulated but, using deterministic contour overlays, also reveals where the tampering occurs. Trained from scratch on CASIA v2.0 (7,492 authentic, 5,123 tampered), the model attains 95.31% accuracy and an F1 score of 0.95, while a classification only ablation reaches 97.8% accuracy at the cost of localization. By eliminating a learnable decoder, the entire pipeline stays below 15.4M trainable parameters, yet still delivers forensic-grade outputs.

Future work will proceed along four complementary lines. First, we plan to fine-tune the model on in the wild datasets such as FaceForensics++ and IMD2020 to improve robustness against unknown compression settings and camera models. Second, knowledge-distillation and post-training quantization will be explored to create a sub-10M-parameter variant suitable for real-time deployment on mobile or edge hardware. Third, we will investigate weakly supervised localization techniques such as class activation maps and attention roll-outs to infer tamper masks without relying on ground-truth contours at test time. Finally, extending the framework to short video clips will leverage temporal coherence for more reliable detection and localization across consecutive frames. Collectively, these directions aim to broaden the applicability of automated image forensics to diverse real-world scenarios.

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