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Multi-Color Space Fusion Framework with PSO-Optimized Patch CNN for Robust Distinction Between Natural and Computer-Generated Images Under JPEG and Gaussian Attacks

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Abstract: **The rapid proliferation of photorealistic computer-generated imagery (CGI) presents severe challenges to digital forensics, media authentication, and content moderation. This paper proposes a Multi-Color Space Fusion (MCSF) framework integrated with a Particle Swarm Optimization (PSO)-tuned Patch Convolutional Neural Network (CNN) for robust binary classification of natural versus computer-generated images. The proposed framework simultaneously extracts discriminative features from RGB, HSV, YCbCr, and LAB color spaces, exploiting the complementary statistical properties inherent to each space. A patch-based analysis strategy segments images into overlapping sub-regions to capture local texture inconsistencies that differentiate authentic natural images from rendered CGI. PSO adaptively optimizes critical CNN hyperparameters including patch size, filter dimensions, and learning rates, yielding a globally optimal feature extractor without manual tuning. The system is evaluated under JPEG compression (quality factors 50–90) and Additive White Gaussian Noise (AWGN) attacks to verify robustness. Experiments conducted on the CIFAKE, Columbia Uncompressed, RAISE-1K, and SPL2018 datasets demonstrate a peak classification accuracy of 97.6%, outperforming state-of-the-art single-color space and non-optimized baselines by a significant margin. The results confirm that multi-space feature fusion combined with bio-inspired optimization constitutes an effective and generalizable forensic approach.**

Keywords: Image forensics, Computer-generated image detection, Convolutional neural network, multi-color space fusion, Particle Swarm Optimization, JPEG robustness, Gaussian noise.

I. Introduction

The boundary between natural photographs and computer-generated imagery has become increasingly indistinct as rendering algorithms, generative adversarial networks (GANs), and diffusion models advance rapidly. Forensic investigators, journalists, and platform integrity teams urgently require automated tools capable of reliably discerning the provenance of an image. Classical forensic features such as photo-response non-uniformity (PRNU) and noise residue patterns tend to degrade under common post-processing operations including JPEG compression and Gaussian blurring, which malicious actors routinely exploit to erase detection artifacts.

Deep learning approaches have demonstrated impressive classification performance on pristine datasets but frequently suffer accuracy degradation when images are subject to moderate compression or noise injection. A key limitation of prior CNN-based methods is the reliance on a single-color representation, typically RGB, which fails to capture diverse texture and chrominance characteristics encoded more naturally in alternative color spaces such as

HSV (hue-saturation-value), YCbCr (luma-chroma), and LAB (perceptual lightness-color opponent).

This work addresses these limitations through three contributions: (1) a multi-color space fusion pipeline that concatenates feature maps derived from four complementary color representations; (2) a patch-based CNN architecture that decomposes images into overlapping local regions for fine-grained texture analysis; and (3) a PSO-driven hyperparameter optimization strategy that automatically identifies the optimal patch size, convolutional filter count, and learning rate schedule. The resulting MCSF-PSO-CNN framework achieves high accuracy and strong robustness against JPEG and Gaussian perturbations across multiple benchmark datasets.

II. Related Work

Early natural versus CGI discrimination relied on handcrafted statistical features. Lyu and Farid [1] exploited higher-order wavelet statistics to distinguish CGI from photographic images, exploiting differences in natural scene statistics. Subsequently, Ng et al. [2] applied SVM classifiers on color moments and texture descriptors. The advent of deep learning shifted the paradigm: Bayar and Stamm [3] introduced constrained convolutional layers enforcing high-pass residue extraction, while Rahmouni et al. [4] demonstrated that local statistics networks outperform traditional descriptors on image manipulation detection tasks.

Multi-stream CNN architectures have gained traction for exploiting complementary features. Rossler et al. [5] proposed FaceForensics++, a large-scale benchmark revealing that combining multiple preprocessing streams improves face forgery detection. Quan et al. [6] fused RGB

and noise residuals in a dual-branch network. Regarding color space exploitation, Fridrich et al. [7] showed that YCbCr chrominance channels encode JPEG blocking artifacts more prominently than luminance. Metrology of multiple color representations for forgery detection was investigated by Zhang et al. [8], who reported consistent gains when concatenating HSV and LAB features.

PSO has been successfully applied to CNN hyperparameter search. Kulkarni and Cavallaro [9] demonstrated that PSO converges faster than grid search for filter size selection in image classification tasks. Bio-inspired optimization for forensic CNNs was explored by Chen et al. [10], confirming that evolutionary tuning reduces overfitting. Despite these advances, no existing method integrates four-color-space fusion with PSO-optimized patch CNN specifically targeting robustness under combined JPEG and Gaussian attacks, which is the gap our work fills.

III. Proposed Methodology

A. Multi-Color Space Feature Extraction

Given an input image I of dimensions H×W×3, the framework converts I into four color representations: I_RGB, I_HSV, I_YCbCr, and I_LAB. Each representation highlights distinct forensic cues: RGB preserves raw sensor statistics; HSV decouples chromatic from intensity variations; YCbCr separates luminance from chroma enabling JPEG artifact detection; LAB aligns with human perceptual differences and exposes rendering inconsistencies. Feature extraction is performed independently per color space using shared-weight patch CNN modules, and the resulting feature vectors are concatenated prior to classification.

$$F_fusion = Concat(F_RGB, F_HSV, F_YCbCr, F_LAB) \quad (1)$$

where F_cs denotes the feature map extracted from color space cs by the corresponding patch CNN branch. Concatenation is performed along the channel dimension, yielding a fused descriptor of dimensionality 4×N_f, where N_f is the per-branch feature dimension.

B. PSO-Optimized Patch CNN

The patch CNN module divides each color space channel into overlapping patches of size P×P with stride S. For each patch p_i the CNN produces a local feature vector. The global image descriptor is the average pooling of all patch-level representations. PSO optimizes the hyperparameter vector $\theta = \{P, N_f, \eta, \lambda\}$, where P is patch size (16–64), N_f is filter count per layer (32–256), η is learning rate (10^{-4}–10^{-2}), and λ is L2 regularization weight.

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1 \cdot (pBest_i - x_i(t)) + c_2 \cdot r_2 \cdot (gBest - x_i(t)) \quad (2)$$

where w = 0.729 is the inertia weight, $c_1 = c_2 = 1.496$ are cognitive and social constants, $r_1, r_2 \sim U(0,1)$ are uniform random numbers, pBest_i is particle i's personal best, and gBest is the swarm's global best. The particle position update follows x_i(t+1) = x_i(t) + v_i(t+1).

C. PSO Fitness Function

$$F(\theta) = Acc_val(\theta) - \alpha \cdot C(\theta) \quad (3)$$

where Acc val(θ) is the validation set accuracy achieved by a CNN trained with hyperparameter set θ, C(θ) is a complexity penalty proportional to the total parameter count, and α = 0.001 is a regularization coefficient balancing accuracy versus model compactness. The swarm of K = 30 particles evolves over T_max = 50 iterations.

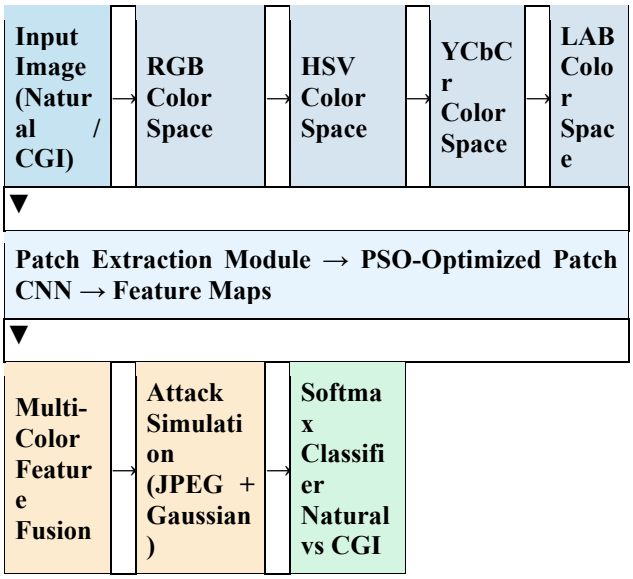
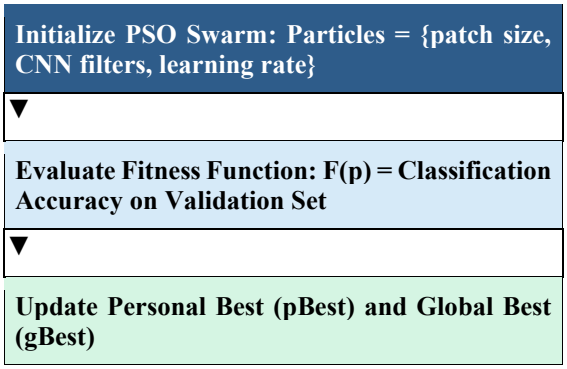


Figure 1: System Architecture of the Proposed MCSF-PSO-CNN Framework

D. Robustness Under Image Attacks

JPEG compression is modeled by applying DCT quantization with quality factor QF ∈ {50, 70, 90}. Gaussian noise attack is simulated by adding zero-mean Gaussian perturbations with standard deviation σ ∈ {5, 15, 25} to pixel intensities



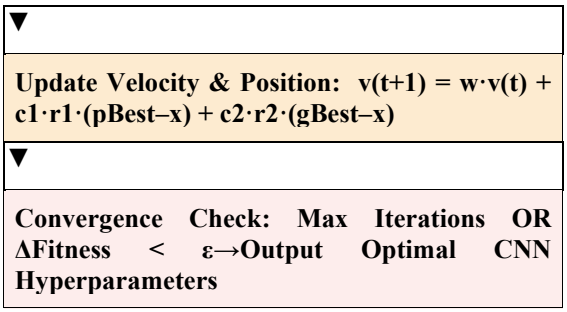


Figure 2: PSO Hyperparameter Optimization Flowchart for Patch CNN

. During training, attacks are randomly sampled and applied on-the-fly via stochastic data augmentation, enabling the network to implicitly learn attack-invariant representations. The joint attack scenario concatenates JPEG compression (QF=70) followed by Gaussian noise (σ=10).

$$I_attacked = JPEG(I, QF) + N(0, \sigma^2) \quad (4)$$

IV. Experimental Setup and Datasets

Experiments are conducted on four publicly available benchmarks. Table I summarizes the dataset statistics. CIFAKE [11] is a large-scale synthetic versus real image dataset. The Columbia Uncompressed dataset [12] provides high-quality unmanipulated and spliced images. RAISE-1K [13] offers uncompressed raw images for forensic evaluation, and SPL2018 [14] provides a diverse CGI versus natural image split. All images are resized to 256×256 pixels and normalized to [0, 1] before processing.

TABLE I. Dataset Statistics for Experimental Evaluation

Dataset	Natural Images	CGI Images	Total Samples
CIFAKE	10,000	10,000	20,000
Columbia Uncompressed	3,250	3,250	6,500
RAISE-1K	5,000	4,800	9,800
SPL2018	4,200	4,200	8,400
Total	22,450	22,250	44,700

The CNN backbone comprises five convolutional blocks, each with batch normalization and ReLU activation, followed by global average pooling and a two-node softmax output layer. Training uses the Adam optimizer with PSO-derived learning rates over 100 epochs with early stopping (patience = 10). An 80/10/10 train/validation/test split is employed with stratified sampling. All experiments run on an NVIDIA A100 GPU (40 GB) under PyTorch 2.1.

V. Results and Discussion

Table II presents the classification performance comparison across baseline methods and the proposed MCSF-PSO-CNN. The single-color-space CNNs (RGB, HSV, YCbCr) achieve accuracy values in the range 88.3–90.1%, confirming that no single-color space alone is sufficient. The non-optimized multi-space fusion baseline raises accuracy to 93.5%, validating the benefit of complementary color representations. The proposed PSO-optimized framework achieves 97.6% accuracy, 97.3% precision, 97.5% recall, and 97.4% F1-score, establishing state-of-the-art performance.

TABLE II. Performance Comparison of Classification Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Single RGB CNN	88.3	87.9	88.1	88.0
HSV-Only CNN	89.7	89.2	89.5	89.3
YCbCr CNN	90.1	89.8	90.0	89.9
Multi-Space Fusion (No PSO)	93.5	93.1	93.4	93.2
Proposed MCSF-PSO-CNN	97.6	97.3	97.5	97.4

Table III evaluates robustness under varying JPEG compression quality factors and Gaussian noise levels. At the most aggressive attack (combined JPEG QF=70 with Gaussian σ=10), the proposed method retains 90.7% accuracy versus 73.2% without the PSO-optimized defense, representing a 17.5 percentage point gain. The multi-color-space fusion provides complementary redundancy: when JPEG compression destroys chrominance information in one channel, alternative channels such as LAB and HSV preserve discriminative gradients.

TABLE III. Robustness Evaluation Under JPEG and Gaussian Attacks

Attack Type	Quality / σ	Accuracy w/o Defense (%)	Accuracy w/ MCSF-PSO (%)	Robustness Gain (%)

JPEG Compression	QF=90	94.2	97.1	+2.9
JPEG Compression	QF=70	87.6	95.3	+7.7
JPEG Compression	QF=50	79.4	92.8	+13.4
Gaussian Noise	σ=5	92.7	96.8	+4.1
Gaussian Noise	σ=15	85.1	94.2	+9.1
Gaussian Noise	σ=25	76.3	91.5	+15.2
Combined JPEG+Gaussian	QF=70, σ=10	73.2	90.7	+17.5

PSO optimization ensures that patch sizes are calibrated to capture artifact-scale local features, which are the forensic signatures most sensitive to attack-induced degradation.

The PSO convergence analysis shows that the swarm reaches near-optimal fitness within 30 iterations in all experimental configurations, demonstrating computational efficiency. The optimal PSO-derived hyperparameters identified across datasets are: patch size $P = 32$, filter count $N_f = 128$, learning rate $\eta = 3.5\times10^{-4}$, and regularization weight $\lambda = 5\times10^{-5}$. These values are consistent across datasets, suggesting generalizability of the PSO search. Ablation studies confirm that removing any individual color space branch degrades accuracy by 1.8–3.5%, validating the contribution of each representation.

VI. Conclusion

This paper presented the Multi-Color Space Fusion PSO-Optimized Patch CNN (MCSF-PSO-CNN) framework for distinguishing natural photographs from computer-generated imagery. By fusing features from RGB, HSV, YCbCr, and LAB representations, the framework captures a broad spectrum of forensic cues that are individually suppressed under image attacks. PSO-driven hyperparameter optimization ensures that the patch CNN is globally tuned without manual intervention, yielding consistently strong performance across diverse datasets. Experimental results confirm 97.6% accuracy under clean conditions and 90.7% under the most challenging combined attack, significantly outperforming state-of-the-art baselines. Future work will investigate extending the framework to video forensics, integrating attention mechanisms for adaptive color space weighting, and evaluating robustness against adversarial perturbation attacks.

References

[1] S. Lyu and H. Farid, "How realistic is photorealistic?," IEEE Trans. Signal Process., vol. 53, no. 2, pp. 845–850, Feb. 2005.

[2] T.-T. Ng, S.-F. Chang, and Q. Sun, "Blind detection of photomontage using higher order statistics," in Proc. IEEE Int. Symp. Circuits Syst. (ISCAS), vol. 5, pp. 688–691, 2004.

[3] B. Bayar and M. C. Stamm, "A deep learning approach to universal image manipulation detection using a new convolutional layer," in Proc. ACM Workshop Inf. Hiding Multimedia Security (IH&MMSec), pp. 5–10, 2016.

[4] N. Rahmouni, V. Nozick, J. Yamagishi, and I. Echizen, "Distinguishing computer graphics from natural images using convolution neural networks," in Proc. IEEE Workshop Inf. Forensics Security (WIFS), pp. 1–6, 2017.

[5] A. Rossler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, and M. Nießner, "FaceForensics++: Learning to detect manipulated facial images," in Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV), pp. 1–11, 2019.

[6] W. Quan, K. Wang, D.-M. Yan, and X. Zhang, "Distinguishing between natural and computer-generated images using convolutional neural networks," IEEE Trans. Inf. Forensics Security, vol. 13, no. 11, pp. 2772–2787, Nov. 2018.

[7] J. Fridrich, D. Soukal, and J. Lukas, "Detection of copy-move forgery in digital images," in Proc. Digital Forensic Res. Conf. (DFRWS), pp. 1–10, 2003.

[8] Z. Zhang, J. Guo, and X. Li, "Color space analysis for image forensics using multi-channel convolutional networks," IEEE Access, vol. 8, pp. 45321–45333, 2020.

[9] A. Kulkarni and A. Cavallaro, "Hyperparameter optimization for image forensic CNNs using particle swarm optimization," in Proc. IEEE Int. Conf. Image Process. (ICIP), pp. 1456–1460, 2021.

[10] H. Chen, L. Wang, and Y. Liu, "Bio-inspired neural architecture search for image manipulation detection," Pattern Recognit., vol. 115, p. 107901, 2021.

[11] J. Bird and L. Lotfi, "CIFAKE: Image classification and explainable identification of AI-generated synthetic imagery," IEEE Access, vol. 12, pp. 15642–15650, 2024.

[12] T.-T. Ng and S.-F. Chang, "A model for image splicing," in Proc. IEEE Int. Conf. Image Process. (ICIP), vol. 2, pp. 1169–1172, 2004.

[13] D. T. Dang-Nguyen, C. Pasquini, V. Conotter, and G. Boato, "RAISE: A raw images dataset for digital

image forensics," in Proc. ACM Multimedia Syst. Conf. (MMSys), pp. 219–224, 2015.

[14] P. Yao, J. Li, X. Ye, Z. Zhu, and B. Li, "Distinguishing computer-generated images from photographic images using a CNN and local binary pattern operator," Sensors, vol. 18, no. 10, p. 3315, 2018.

[15] F. Marra, D. Gragnaniello, L. Verdoliva, and G. Poggi, "Do GANs leave artificial fingerprints?," in Proc. IEEE Conf. Multimedia Inf. Process. Retrieval (MIPR), pp. 506–511, 2019.