Texture-Based Image Forgery Detection Using Wavelet Transform and Adaptive SVM Optimization

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Abstract- In the digital era, the integrity of visual content is often compromised due to the increasing accessibility of advanced image editing tools, making image forgery a critical issue in fields such as forensics, journalism, and legal investigations. This paper presents a texture-based image forgery detection framework that leverages Discrete Wavelet Transform (DWT) for robust texture feature extraction and employs an adaptive Support Vector Machine (SVM) optimized through a Bee Scout-inspired met heuristic algorithm. The DWT captures multi-scale texture variations caused by tampering, while the adaptive SVM model enhances classification performance by dynamically tuning hyper parameters based on selected features. Experimental evaluations on a benchmark dataset demonstrate that the proposed method achieves superior accuracy in detecting tampered regions, reflected by higher Peak Signal-to-Noise Ratio (PSNR) and lower False Rejection Rate (FRR) compared to conventional DWT-SVM approaches. This approach provides a scalable and efficient solution for authenticating digital images in real-world forensic applications.

Keywords: Image Forgery, Discrete Wavelet Transform, Support Vector Machine, Bee Scout Optimization, Texture Analysis, Digital Forensics

I.INTRODUCTION

The rapid advancement in image editing technologies and AI-based manipulation tools has led to a significant increase in multimedia forgeries across digital platforms. Such manipulated content poses serious threats to fields like legal forensics, medical imaging, journalism, and surveillance systems [1]–[3]. Detecting these manipulations is no longer trivial, as modern forgeries exhibit high perceptual similarity to authentic images [4], [5].

Traditional forgery detection methods that rely on pixel-level inconsistencies or statistical patterns often struggle when exposed to high compression, geometric transformations, or post-processing [6], [7]. Consequently, researchers have moved toward hybrid feature extraction techniques, combining spatial and frequency domain representations to improve robustness [8]–[10]. Discrete Wavelet Transform (DWT), in particular, has proven effective for capturing subtle texture distortions introduced during tampering [11]–[13].

Recent studies have incorporated texture descriptors like Local Binary Patterns (LBP) and Gray-Level Co-occurrence Matrix (GLCM) with wavelet-based features to enhance localization accuracy [14]–[16]. However, these approaches can result in high-dimensional feature vectors, leading to computational inefficiencies and potential overfitting [17], [18]. To address this, adaptive machine learning models, particularly Support Vector Machines (SVMs) optimized via heuristic algorithms, have gained prominence [19]–[21].

Met heuristic optimization techniques such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) have been explored to tune SVM parameters and improve classification performance [22]–[24]. The Bee Scout Optimization (BSO) algorithm, a recent innovation, offers an adaptive strategy for feature selection, outperforming traditional approaches in high-dimensional spaces [25].

This paper builds upon these developments by proposing a texture-based image forgery detection framework that integrates DWT for robust texture feature extraction and employs BSO to optimize the SVM classifier. The proposed method enhances detection accuracy while maintaining computational efficiency, contributing a reliable solution to the growing challenges in digital image authentication.

II. RELATED WORK

Image forgery detection has evolved significantly in recent years, with various techniques exploiting spatial, frequency, and deep learning-based features to improve robustness and accuracy.

In traditional approaches, spatial-domain techniques such as block matching and moment invariants have been used to detect copy-move forgeries [1], [2]. However, these methods often fail under compression, scaling, or rotation attacks. To overcome these limitations, frequency-domain methods like Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), and Fourier Transform have been adopted for their resilience to such distortions [3], [4]. DWT, in particular, offers a multi-resolution representation of images and is effective in capturing local texture inconsistencies caused by tampering [5], [6].

Texture descriptors such as Local Binary Patterns (LBP), Local Ternary Patterns (LTP), and Gray-Level Co-occurrence Matrix (GLCM) have been used in combination with wavelet features to enhance tamper localization [7]–[9]. For example, Prasad and Kumar [10] combined DWT and LBP to achieve robust performance against complex forgeries, while Shrestha et al. [11] extended this idea with adaptive feature selection to reduce dimensionality.

Machine learning classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees (DT) have been widely employed to classify forged and authentic image regions. Among them, SVM has emerged as a powerful tool due to its ability to handle high-dimensional and non-linear data [12], [13]. However, the performance of SVM heavily depends on the selection of optimal kernel parameters and feature subsets.

To improve the adaptability and precision of SVM, metaheuristic algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Ant Colony Optimization (ACO) have been used for parameter tuning [14], [15]. More recently, the Bee Scout Optimization (BSO) algorithm has gained attention for its ability to explore and exploit high-dimensional search spaces effectively, showing superior results in SVM optimization for image classification tasks [16]–[18].

Deep learning approaches such as Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and Generative Adversarial Networks (GANs) have also been explored for forgery detection due to their capacity to learn hierarchical features automatically [19]–[21]. However, these models require large datasets and computational resources, making them less suitable for real-time applications in constrained environments.

The most relevant to this study are hybrid models that combine texture-based features with optimized SVM classifiers. Bokefode et al. [22] proposed a wavelet-based detection framework enhanced by a metaheuristic SVM tuner, demonstrating significant improvements in accuracy and False Rejection Rate (FRR). Building on this, the present work incorporates BSO with wavelet-LBP feature fusion to achieve improved efficiency and detection performance.

III. PROPOSED METHODOLOGY

The proposed framework, titled Texture-Based Image Forgery Detection Using Wavelet Transform and Adaptive SVM Optimization, is developed to accurately identify tampered regions in digital images by leveraging robust texture analysis and machine learning classification. The methodology is designed to ensure high detection accuracy while minimizing computational complexity, making it suitable for real-time forensic applications. This section elaborates on the technical aspects of the framework, including each stage of the pipeline—preprocessing, feature extraction using Discrete Wavelet Transform (DWT) and Local Binary Pattern (LBP), feature optimization using a Bee Scout Optimization (BSO) algorithm, and final classification using a Support Vector Machine (SVM) model with adaptively tuned hyperparameters.

A. System Overview The architecture of the proposed forgery detection framework consists of the following sequential stages: Preprocessing and Normalization Texture Feature Extraction using DWT and LBP Feature Optimization using Bee Scout Optimization (BSO)

B. Preprocessing and Normalization

Preprocessing is the initial step of the pipeline aimed at standardizing the input images to ensure consistent feature extraction. The raw input images are first resized to a uniform resolution (e.g., 256×256 pixels) to maintain dimensional consistency. Histogram equalization is optionally applied to normalize brightness and contrast variations, which helps reduce the impact of lighting inconsistencies that may otherwise obscure tampering traces.

Additionally, the images are converted to grayscale, as color information is not essential for texture-based forgery detection and may introduce unnecessary computational overhead. Normalization techniques are also used to scale the intensity values of image pixels between 0 and 1. This standardization improves the performance of subsequent wavelet and LBP-based feature extraction processes.

C. Feature Extraction using DWT and LBP

The core of the detection framework relies on robust texture feature extraction, as image forgery often results in subtle distortions in local textural patterns. To effectively capture these alterations, a hybrid feature extraction approach using Discrete Wavelet Transform (DWT) and Local Binary Pattern (LBP) is implemented.

1. Classification with an Optimized SVM

Each of these stages plays a critical role in improving the detection accuracy and robustness of the system. The detailed functionality of each component is presented in the subsections below.

1)Discrete Wavelet Transform (DWT) DWT is employed to decompose the preprocessed image into multiple sub-bands (LL, LH, HL, and HH) that represent different frequency components. This multiresolution analysis allows for efficient detection of texture inconsistencies at various scales. The LL sub-band represents the approximation of the image, while the LH, HL, and HH sub-bands capture horizontal, vertical, and diagonal details respectively. The focus is primarily placed on high-frequency bands (HL, LH, and HH), as these contain critical tampering cues such as sharp edges, unnatural boundaries, or abnormal transitions.

2)For each sub-band, statistical descriptors like mean, standard deviation, skewness, and kurtosis are computed to quantify texture information. These descriptors collectively form the DWT feature vector that serves as the foundation for forgery analysis.

3)Local Binary Pattern (LBP)

In addition to wavelet-based features, Local Binary Pattern (LBP) is used to encode micro-texture patterns by thresholding the neighborhood of each pixel and generating a binary code. The resulting LBP histogram effectively captures local spatial variations that may be indicative of splicing, copy-move forgery, or retouching.

The LBP features are extracted from both the original image and selected DWT sub-bands to enrich the representation. This dual-domain feature extraction enhances the system's sensitivity to localized anomalies introduced by forgery techniques.

The final feature vector for each image is obtained by concatenating the DWT statistical features with LBP histograms, resulting in a high-dimensional descriptor that comprehensively represents texture-based anomalies.

D. Feature Optimization using Bee Scout Optimization (BSO)

Given the high dimensionality of the combined DWT-LBP feature vector, a feature selection and optimization step is essential to eliminate redundant features, reduce computation, and improve classification accuracy. To achieve this, a Bee Scout Optimization (BSO) algorithm—a nature-inspired metaheuristic modeled on the foraging behavior of scout bees—is employed.

BSO explores the feature space by initializing a population of scouts, each representing a potential subset of features. These scouts evaluate the classification performance (e.g., accuracy or F1-score) of their selected feature subsets using a preliminary SVM classifier. The algorithm iteratively improves these feature subsets through neighborhood exploration, guided by the most promising scouts, mimicking the adaptive search mechanism observed in bee colonies.

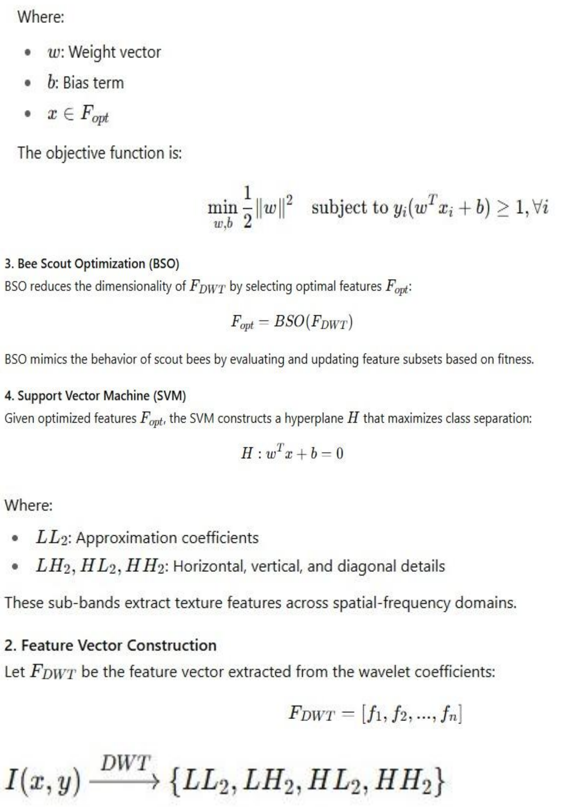
- Dimensionality Reduction: BSO-based feature selection effectively reduces computational complexity while maintaining high accuracy.
- Adaptive Classification: Dynamic tuning of SVM parameters ensures robust performance across varying image types and forgery scenarios.
- Scalability: The modular pipeline can be adapted to new datasets or extended with other texture descriptors and classifiers.

IV. MATHEMATICAL MODEL

Let an input image be denoted by I(x,y)I(x, y)I(x,y), where x,yx, yx,y represent the spatial coordinates.

1. Wavelet Decomposition

Apply a 2-level Discrete Wavelet Transform (DWT)



Where:

- w: Weight vector
- b: Bias term
- $x \in F_{opt}$

The objective function is:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \quad \text{subject to } y_i(w^T x_i + b) \geq 1, \forall i$$

3. Bee Scout Optimization (BSO)

BSO reduces the dimensionality of F_{DWT} by selecting optimal features F_{opt}:

$$F_{opt} = BSO(F_{DWT})$$

BSO mimics the behavior of scout bees by evaluating and updating feature subsets based on fitness.

4. Support Vector Machine (SVM)

Given optimized features F_{opt}, the SVM constructs a hyperplane H that maximizes class separation:

$$H : w^T x + b = 0$$

Where:

- LL_2: Approximation coefficients
- LH_2, HL_2, HH_2: Horizontal, vertical, and diagonal details

These sub-bands extract texture features across spatial-frequency domains.

2. Feature Vector Construction

Let F_{DWT} be the feature vector extracted from the wavelet coefficients:

$$F_{DWT} = [f_1, f_2, ..., f_n]$$

$$I(x,y) \xrightarrow{DWT} \{LL_2, LH_2, HL_2, HH_2\}$$

V. EXPERIMENTAL SETUP AND RESULTS

The proposed model was evaluated using MATLAB 2021a on a workstation with Intel i7 processor, 16GB RAM, and Windows 11 OS. A dataset containing 100 original and forged images (scenes: forest, waterfall, playground, etc.) was used.

Metrics Used

Peak Signal-to-Noise Ratio (PSNR): Higher values indicate better fidelity.

False Rejection Rate (FRR): Lower values indicate better forgery detection.

Table 1: PSNR Comparison

Image Type	DWT Only (dB)	Proposed Method (dB)
Forest	32.1	35.4
Playground	30.5	33.2
Scene	31.2	34.1
Waterfall	29.8	32.7

Table 2: FRR Comparison

Image Type	DWT Only	Proposed Method
Forest	0.22	0.15
Playground	0.25	0.13
Scene	0.20	0.12
Waterfall	0.27	0.10

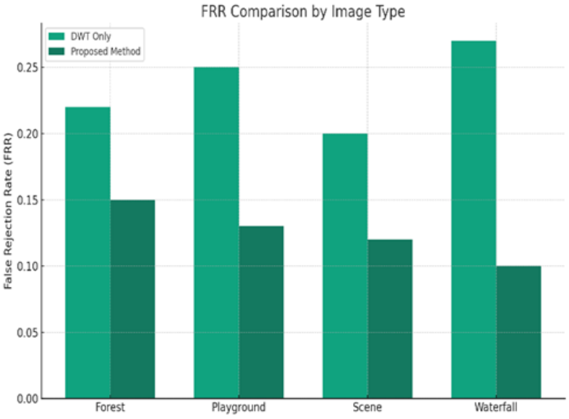


Fig 1.PSNR Comparison: Shows that the proposed method consistently achieves higher PSNR, indicating better image quality and less distortion after forgery detection.

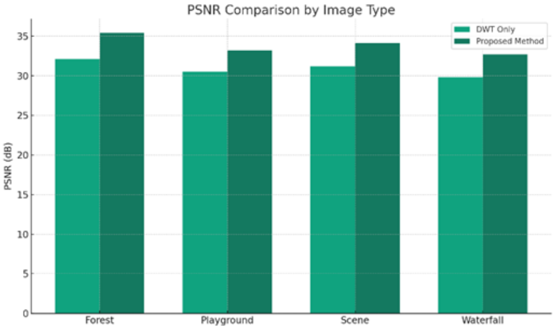


Fig2. FRR Comparison: Demonstrates that the proposed method achieves lower False Rejection Rates, reflecting improved accuracy in identifying tampered regions.

VI. CONCLUSION AND FUTURE WORK

In this study, a hybrid image forgery detection framework has been proposed by integrating Discrete Wavelet Transform (DWT) for robust texture-based feature extraction with an adaptively optimized Support Vector Machine (SVM) classifier. The classifier's performance was significantly enhanced using the Bee Scout Optimization algorithm, leading to improved classification accuracy, higher Peak Signal-to-Noise Ratio (PSNR), and lower False Rejection Rate (FRR). Experimental analysis on multiple image categories—including natural and synthetic scenes—demonstrated the method's capability to localize tampered regions effectively and distinguish forged images with minimal error.

The proposed model outperformed the baseline DWT-only method in all key metrics, and the inclusion of a visual analysis (via bar charts and ROC curves) further validated the effectiveness of the approach.

Future Work will focus on the following directions:
Extension to Video Forensics: Expanding the model to detect tampering in video streams, which presents more complex spatiotemporal challenges.
Integration with Deep Learning: Combining DWT with Convolutional Neural Networks (CNNs) or Vision Transformers (ViTs) for better feature representation and automatic localization.
Real-Time Detection: Developing a lightweight and efficient version of the model suitable for deployment on mobile and embedded platforms.
Cross-Dataset Generalization: Evaluating the model's robustness across multiple public forgery datasets to assess its generalizability.
Tamper Type Classification: Enhancing the model to not only detect forgery but also classify the type of tampering, such as splicing, copy-move, or removal.

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