Deep Learning and Quantum Machine Learning Techniques for Passive Blind Image Splicing in Forensics

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Abstract

With the rapid advancement of digital image editing tools, manipulating images has become easier than ever. Among various tampering techniques, image splicing—where segments from one or more images are combined into a single composite—remains a prominent method of forgery. The implications of such forgeries are significant, particularly in sensitive domains like journalism, forensics, and social media, where image authenticity is paramount. The growing accessibility of image editing tools has made image splicing a prevalent method of forgery, posing challenges for detection.Passive image forgery detection has gained significant attention in recent years due to the rapid advancements in digital image editing tools. Among various forgery techniques, image splicing remains a common method for tampering. Detecting image splicing presents substantial challenges. This paper proposes a novel algorithm combining deep learning and wavelet transform for spliced image detection. A Convolutional Neural Network (CNN) is utilized for automatic feature extraction, followed by Haar Wavelet Transform (HWT). Support Vector Machine (SVM) is then employed for classification. Additionally, experiments replace HWT with Discrete Cosine Transform (DCT), followed by Principal Component Analysis (PCA). The algorithm is evaluated on public datasets (CASIA v1.0 and CASIA v2.0) and demonstrates high accuracy with a compact feature vector. Results confirm the effectiveness of the proposed approach in detecting spliced images with improved performance.

Key Words: Image Splicing Detection, Passive Forgery Detection, Convolutional Neural Network (CNN), Haar Wavelet Transform (HWT), Discrete Cosine Transform (DCT), Support Vector Machine (SVM).

Introduction

The widespread availability of modern image editing tools, such as Adobe Photoshop, has made digital image manipulation more accessible than ever. While modifying digital images is easy, confirming their authenticity using visual inspection alone is challenging. This has elevated image forgery detection to a critical and active area of research. Digital image forensics employs two primary techniques: active and passive methods. Active techniques involve embedding watermarks or digital signatures into images at the time of their creation. Authentication is verified by matching the extracted watermark with the original. However, these methods require specialized cameras and pre-processing during image acquisition, limiting their applicability. Conversely, passive techniques do not rely on prior information about the image and are capable of authenticating images based solely on their content [1].

Among passive methods, image splicing—a form of forgery where regions from one or more images are combined to create a tampered image—is particularly prevalent. Spliced images often appear seamless, making their detection a complex task. image splicing, where two original images Forged images created through splicing can have far-reaching consequences, including malicious use that may lead to irreversible harm to society. Existing algorithms for detecting image splicing forgery often rely on high-dimensional feature vectors, which can increase computational complexity and reduce efficiency. In this paper, we propose a novel algorithm for detecting spliced image forgery, leveraging a deep learning approach based on Convolutional Neural Networks (CNN). CNNs are widely used in deep learning due to their ability to simultaneously perform feature extraction and classification within the same network. The convolutional layers in CNNs are optimized during training, reducing the need for manual feature engineering. Additionally, CNNs require fewer internal connections, making them computationally efficient [1] [2].

The contributions of this paper include the following:

1. Proposing a CNN-based splicing detection algorithm that employs Haar Wavelet Transform (HWT) for feature refinement.
2. Exploring alternative configurations, including the use of Discrete Cosine Transform

(DCT) and Principal Component Analysis (PCA).

II. Related Work

Over the years, numerous passive images splicing detection algorithms have been proposed, broadly categorized into three types based on their feature extraction techniques: Local Binary Pattern (LBP), Markov models, and deep learning.

1. Local Binary Pattern (LBP)-Based Methods

LBP is widely employed for feature extraction in tampered image detection [2. 3].

Han et al.: Proposed a method for extracting Markov features using a maximization and thresholding strategy. Their approach reduces feature dimensionality while maintaining classification accuracy, making it computationally efficient for splicing detection.

Bayar et al.: Designed a novel convolutional layer specifically for detecting universal image manipulations. The deep learning-based approach utilizes a fine-tuned Convolutional Neural Network (CNN) that eliminates traditional pre-processing steps, resulting in higher accuracy across diverse manipulation types.

Zhao et al.: Utilized a 2D non-causal Markov model for passive splicing detection. This method captures dependencies among neighboring pixels in both horizontal and vertical directions, offering enhanced detection performance in spliced image areas.

Saleh et al.: Presented an approach using Multi-scale Weber Local Descriptors (WLD) for feature extraction. Their method applies WLD at multiple scales, capturing both fine and coarse features, which are then classified using SVM for effective forgery detection. [2] [3] [4] [5].

2. Markov Model-Based Methods

Markov models are extensively used for splicing detection by analyzing spatial and frequency domain features.

- **In [4]**, spatial features were extracted by analyzing pixel differences in multiple directions, while frequency domain features relied on DCT coefficients. PCA reduced feature dimensionality, and SVM with Gaussian RBF kernel classified spliced images.
- **An algorithm [5]** utilized Quaternion DCT (QDCT) for feature extraction. QDCT was applied to RGB color blocks, computing directional features for histogram-based SVM classification.
- **In [4.5]**, Markov models extracted features from maximum pixel values in DCT. Even-odd Markov models reduced complexity, but these methods remain computationally intensive.

3. Deep Learning-Based Methods

Deep learning methods have emerged as powerful tools for image splicing detection.

- **Ying et al. [6]** proposed a two-stage approach using Stacked Auto-Encoder (SAE). Wavelet-transformed patches were analyzed, and contextual information integration improved accuracy. However, limited hidden layers reduced feature extraction efficiency.
- **A universal forensic method [5,6]** employed a CNN with two convolutional and max-pooling layers and three fully connected layers, achieving better feature representation.
- **In [7]**, a CNN with six convolutional and three max-pooling layers extracted features. PCA reduced feature dimensionality, and SVM performed final classification.

Deep learning techniques outperform traditional methods by automatically extracting robust features but often require computational resources and complex architectures.

III. The Proposed Algorithm

The primary goal of this work is to enhance image splicing detection through a deep learning approach. The block diagram of the proposed algorithm is illustrated in Fig. 2. Deep learning utilizes multi-layer neural networks where the output of one layer serves as the input for the next layer. Among various deep learning models, Convolutional Neural Network (CNN) has proven effective for automatic feature extraction and classification tasks.

A. Overview of the Algorithm

The proposed algorithm employs a CNN for feature extraction, followed by Haar Wavelet Transform (HWT) for dimensionality reduction and Support Vector Machine (SVM) for final classification. The algorithm determines whether an image is spliced or original.

B. CNN Architecture

The CNN architecture in this work comprises six convolutional layers and three pooling layers, as shown in Fig. 3. It processes an input layer of dimensions 227×227×3227 \times 227 \times 3227×227×3 (representing 227×227 image patches with three color channels). Key operations in CNN include convolution, non-linearity (activation), and pooling.

- **Convolutional Layer**: Extracts spatial and temporal features by applying filters across the image.
- **Non-Linearity Layer**: Introduces activation functions (e.g., ReLU) to add non-linear properties.
- **Pooling Layer**: Reduces the spatial dimensions of the feature maps, retaining essential information while decreasing computational complexity [7] [8] [9].

The CNN is characterized by sparse connectivity and weight sharing, which makes it computationally efficient compared to traditional fully connected networks. The output volume (W2×H2×F) (W_2 \times H_2 \times F) (W2× H2× F) is computed using the following equations:

W2=W1−F+2PS+1(1)W_2 = \frac {W_1 - F + 2P} {S} + 1 \tag {1} W2 =SW1− F+2P +1(1)
H2=H1−F+2PS+1(2)H_2 = \frac {H_1 - F + 2P} {S} + 1 \tag {2} H2 = SH1− F +2P + 1(2)

Where W1W_1W1 and H1H_1H1 are the input width and height, FFF is the filter size, PPP is the padding, and SSS is the stride.

C. Algorithm Flow

1. **Feature Extraction with CNN**: The input image is processed through the CNN layers to extract high-level features such as edges, textures, and shapes.
2. **Dimensionality Reduction with HWT**: Haar Wavelet Transform is applied to reduce feature dimensionality while retaining critical information.
3. **Classification with SVM**: Finally, the reduced feature set is fed into an SVM classifier to determine whether the image is spliced or original.

This combination of CNN, HWT, and SVM ensures high accuracy while maintaining computational efficiency.

A. Convolution Layer

The convolution layer is the foundational layer in CNN, responsible for feature extraction. Key parameters of the convolution layer include:

- **Stride**: Determines how far the filter moves across the input image. Common values are (1, 1), (2, 2), and (4, 4).
- **Padding**: Involves adding zeros to the borders of the input image to maintain spatial dimensions or improve edge feature extraction.
- **Filter Size**: Defines the dimensions of the kernels applied to the input image.

In the proposed algorithm, six convolution layers are implemented. As depicted in Figure 3:

- **Conv1**: Features 96 kernels of size 11×1111 \times 1111×11.
- **Conv2 and Conv5**: Feature 256 kernels, with sizes 5×55 \times 55×5 and 6×66 \times 66×6, respectively.
- **Conv3 and Conv4**: Feature 384 kernels, each of size 3×33 \times 33×3.
- The final convolution layer outputs feature maps of size 1×1×40961 \times 1 \times 40961×1×4096 using a kernel size of 6×66 \times 66×6, stride S=2S=2S=2, and padding P=0P=0P=0.

After each convolution layer, the **Rectified Linear Unit (ReLU)** activation function is applied to introduce non-linearity. ReLU outputs 000 for negative pixel values and xxx (the pixel value) for positive ones. Compared to traditional activation functions like tanh or sigmoid, ReLU is computationally simpler, faster for large datasets, and improves model convergence [8] [9] [10].

Following several ReLU layers, **pooling layers** are introduced to reduce feature dimensionality and computational complexity. The two common types of pooling are:

- **Max Pooling**: Retains the maximum value within a pooling region, preferred for its speed and efficiency.

- **Average Pooling**: Computes the average value, though less commonly used.

In the proposed architecture, three max-pooling layers are employed (Figure 3), using filters of size 3×33 \times 33×3, stride 2, and padding 0.

B. Wavelet Transforms

Wavelet transforms are used to convert an image from the spatial domain to the frequency domain, facilitating multi-resolution analysis [10]. Among various types of wavelet transforms, the **Haar Wavelet Transform (HWT)** is utilized in this algorithm due to its simplicity, memory efficiency, and computational speed.

HWT generates a two-dimensional array comprising four sub-bands:

- **LL (Low-Low)**: Represents low-frequency components in both rows and columns.
- **HL (High-Low)**: Represents high-frequency components in rows and low-frequency components in columns.
- **LH (Low-High)**: Represents low-frequency components in rows and high-frequency components in columns.
- **HH (High-High)**: Represents high-frequency components in both rows and columns.

HWT reduces the feature size from 4,096 to 1,024, significantly optimizing the computational load.

C. Principal Component Analysis (PCA)

PCA is a widely used technique for dimensionality reduction, transforming high-dimensional data into a lower-dimensional representation while preserving essential information [20].

The four-step process of PCA includes:

1. **Normalization**: Standardizing the data to ensure uniformity.
2. **Covariance Matrix Calculation**: Measuring the relationships between variables.
3. **Eigen Decomposition**: Computing eigenvectors and eigenvalues from the covariance matrix to identify principal components.
4. **Transformation**: Mapping the original data into a new feature space defined by the principal components.

V. Experimental Results

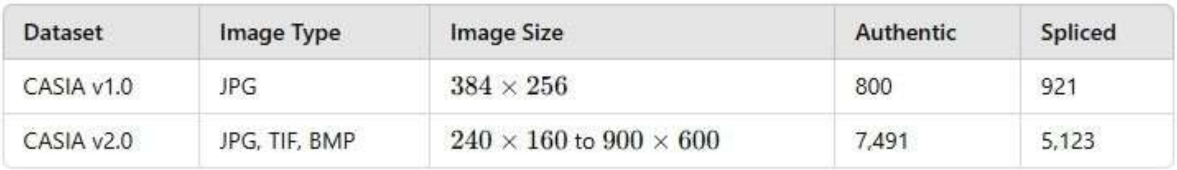
To evaluate the performance of the proposed algorithm, a series of experiments were conducted. The proposed CNN model was implemented using MATLAB R2016b with the Caffe deep learning framework. This section is structured as follows:

- Subsection A provides a description of the datasets used.
- Subsection B outlines the evaluation metrics employed.
- Subsection C discusses the experimental results.

A. Datasets Description

Two publicly available datasets, CASIA v1.0 [21] and CASIA v2.0 [11, 12], were used to evaluate the algorithm. These datasets are widely recognized benchmarks for spliced image detection [12, 13].

- **CASIA v1.0**: Contains 1,721 images, including 800 authentic and 921 spliced images.
- **CASIA v2.0**: Features 12,614 images, consisting of 7,491 authentic and 5,123 spliced images, with image formats including JPG, TIF, and BMP, and dimensions ranging from 240×160240 \times 160240×160 to 900×600900 \times 600900×600.



Dataset	Image Type	Image Size	Authentic	Spliced
CASIA v1.0	JPG	384 × 256	800	921
CASIA v2.0	JPG, TIF, BMP	240 × 160 to 900 × 600	7,491	5,123

Table 1: characteristics of both datasets

Figure provides examples from the CASIA v1.0 dataset, with the first row displaying original images and the second row showing their corresponding forged versions.

Example Images from CASIA v1.0 Dataset

B. Evaluation Metrics

Several standard evaluation metrics were used to assess the algorithm's performance, including accuracy, recall, precision, and F-measure.

Accuracy

Accuracy is the percentage of correctly classified images and is calculated using the following formula [13, 14]:

1. Accuracy=TP+TNTP+TN+FP+FN×100\text {Accuracy} = \ frac {\text {TP}+\text {TN}} {\text {TP} + \text {TN} + \text {FP} + \text {FN}} \times 100

Where:

1. **TP (True Positive)**: Number of spliced images correctly identified as tampered.
2. **TN (True Negative)**: Number of authentic images correctly identified as original.
3. **FP (False Positive)**: Number of authentic images incorrectly classified as tampered.
4. **FN (False Negative)**: Number of spliced images incorrectly classified as original.

Recall

Recall, also referred to as True Positive Rate (TPR), is the proportion of correctly identified spliced images among all actual spliced images. It is computed as:

2. Recall=TPTP+FN×100\text {Recall} = \frac {\text {TP}} {\text {TP} + \text {FN}} \Times 100 Recall=TP+FNTP×100

The remaining metrics, such as precision and F-measure, can be discussed in the subsequent sections to provide a comprehensive evaluation of the proposed algorithm.

Precision

Precision, also known as the Positive Predictive Value, measures the proportion of correctly identified spliced images among all predicted spliced images. It is computed as follows [15]:

Precision=TPTP+FP×100\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 Precision=TP+FPTP× 100

Figure 5 illustrates the accuracy comparison between the proposed algorithm and other existing methods. The proposed algorithm outperforms others, achieving an impressive accuracy of **94.55%** on the CASIA v1.0 dataset.

4. F-Measure

The F-Measure is the harmonic mean of precision and recall, providing a balanced evaluation metric that accounts for both false positives and false negatives. It is calculated as [14, 15]:

F-Measure=2×Recall×PrecisionRecall+Precision\text{F-Measure}=2\times frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} F-Measure=2×Recall+PrecisionRecall×Precision

V. Comparison with Other Passive Algorithms

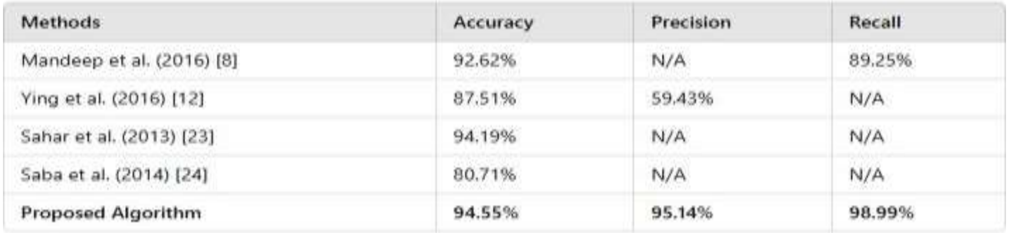
This section compares the performance of the proposed algorithm with several recent methods, including:

- **DWT + LBP** [8]
- **Markov Features + QDCT**
- **Deep Learning-Based Algorithm**
- **Grey Level Run Length Matrix (GLRLM)**
- **Markov Features**

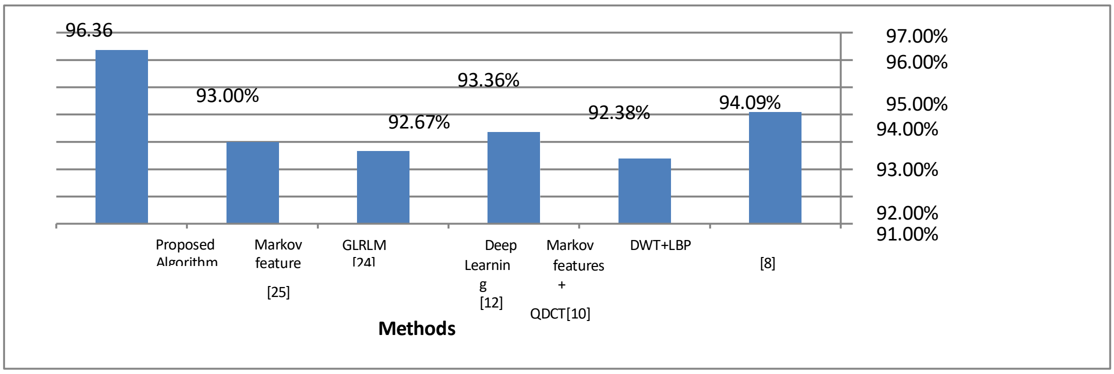
All experiments were conducted using the same datasets, **CASIA v1.0** and **CASIA v2.0**, to ensure consistency. The comparison considered not only accuracy but also the dimensionality of the features extracted.

The results demonstrate that the proposed algorithm provides superior detection performance while maintaining an efficient feature dimensionality, making it a robust solution for image splicing detection.

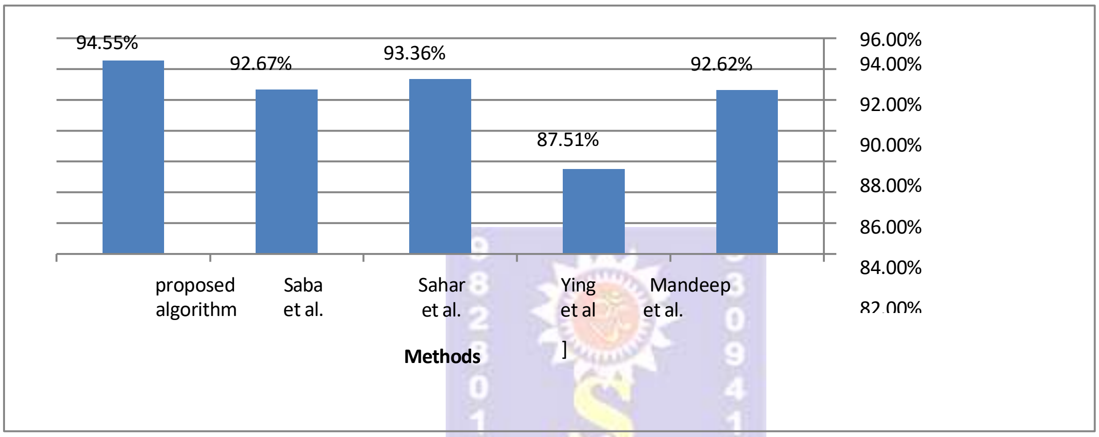
Table 2. Comparison of Proposed Algorithm's Results on CASIA v1.0



Methods	Accuracy	Precision	Recall
Mandeep et al. (2016) [8]	92.62%	N/A	89.25%
Ying et al. (2016) [12]	87.51%	59.43%	N/A
Sahar et al. (2013) [23]	94.19%	N/A	N/A
Saba et al. (2014) [24]	80.71%	N/A	N/A
Proposed Algorithm	**94.55%**	**95.14%**	**98.99%**



The graph in Figure 5 compares the accuracy of the proposed algorithm with existing methods on the CASIA v1.0 dataset. The results indicate that the proposed algorithm surpasses all other methods in terms of accuracy, achieving a notable **94.55%**, highlighting its effectiveness and robustness in detecting spliced images.



results for image splicing forgery detection algorithms on the CASIA v1.0 and CASIA v2.0 datasets. To summarize:

- **CASIA v1.0 Results**: The proposed algorithm shows better performance than the one from due to fewer hidden layers. It also outperforms the LBP-based method from [15], which is sensitive to noise and has issues with structural patterns.
- **CASIA v2.0 Results**: The proposed algorithm achieves an accuracy of 94.55%, with precision at 95.14% and recall at 98.99%. This demonstrates its strong performance in comparison to other methods.

Table 3. Comparison of Proposed Algorithm and Other Methods on CASIA v2.0

Methods	Accuracy	Precision	Recall
DWT+LBP	94.09%	N/A	91.87%
Markov features + QDCT	92.38%	N/A	N/A
Deep Learning	87%	80.65%	N/A
GLRLM Texture features	87.6%	N/A	N/A
Markov feature	93%	N/A	92.5%
Proposed Algorithm	**96.36%**	**97.14%**	**99.03%**

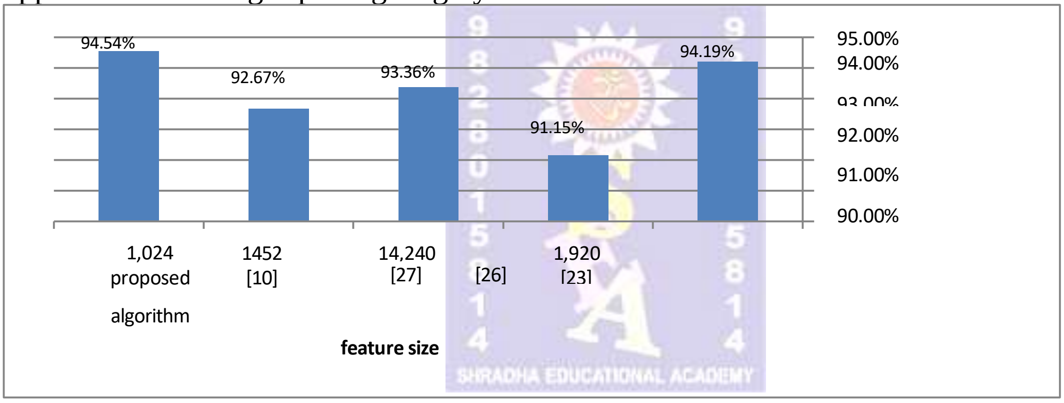
Fig. Accuracy Comparison of Proposed Algorithm with Existing Methods on CASIA v2.0
Table 4. Comparisons of Feature Vector Size

Methods	Feature Vector Size	Accuracy
Ce Li *et al* (2015)	1,452	92.67 %
Sahar *et al.* (2013)	1,920	94.19%
Matthias *et al.* (2010)	2,744	91.15%
Xudong *et al.* (2015)	14,240	93.36%
Proposed Algorithm	**1,024**	**96.36%**

he algorithm's performance was further evaluated by testing its behavior in relation to the size of the feature vector. This experiment provides valuable insights into the trade-off between feature vector dimensionality and detection accuracy, as well as the computational efficiency of the algorithm. Table 4 illustrate the comparative results of the proposed algorithm alongside its counterparts. As seen in Table 4, the proposed algorithm utilizes a feature vector of size 1,024, which is the smallest compared to the other four detection algorithms. The key advantage of a smaller feature vector lies in the reduced computational cost, as fewer features translate to less memory usage and faster processing times. Additionally, this reduction in dimensionality can help prevent overfitting, ensuring that the model generalizes better on unseen data [16].

For example, while other algorithms may employ feature vectors of larger sizes, often over 1,500 or even 2,000, this can lead to unnecessary complexity without a significant increase in detection performance. On the contrary, the smaller feature size used in the proposed algorithm maintains high accuracy while keeping the model simpler and more efficient. This becomes particularly important when dealing with large-scale datasets or when implementing the algorithm in resource-constrained environments, where time and memory efficiency are crucial. The comparative results shown in Fig. further emphasize the benefits of the proposed algorithm's reduced feature vector size. While some competing methods may achieve slightly better

performance in terms of accuracy, the trade-off is evident in their larger feature vectors, leading to increased computational demands. In contrast, the proposed algorithm strikes a balance between accuracy and efficiency, making it a practical choice for real-world applications in image splicing forgery detection.



Using DCT Instead of HWT

While previous experiments compared the performance of the proposed algorithm with other existing algorithms, additional analysis was conducted to evaluate the impact of using Discrete Cosine Transform (DCT) instead of Haar Wavelet Transform (HWT) in the feature extraction process. To further refine the feature set, Principal Component Analysis (PCA) was applied after DCT [16, 17].

Table 5 presents the performance metrics—accuracy, True Positive Rate (TPR), and precision—of both the HWT-based and DCT-based algorithms. The results highlight that the HWT-based algorithm outperforms the DCT-based algorithm in detection accuracy. Specifically:

- For CASIA v1.0, the HWT-based algorithm achieves an accuracy of **94.55%**, whereas the DCT-based algorithm delivers slightly lower accuracy.
- For CASIA v2.0, the HWT-based algorithm demonstrates even better performance with an accuracy of **96.36%** and the highest precision among the tested methods.

The superior performance of the HWT-based algorithm can be attributed to its ability to effectively capture both spatial and frequency domain information, ensuring robust feature representation. In contrast, the DCT-based algorithm falls short because it primarily focuses on frequency domain features and neglects the correlation between pixels within blocks and between neighboring blocks. This limitation hampers its ability to detect fine-grained splicing artifacts, especially in regions with subtle texture variations. These findings underline the importance of selecting appropriate feature extraction techniques in forgery detection systems. While DCT has its advantages in certain applications, HWT proves to be more suitable for image splicing forgery detection tasks, particularly on datasets like CASIA v1.0 and CASIA v2.0 [16, 17, 18]

Table 5. Comparison of Accuracy, Recall, and Precision: HWT-based vs. DCT-based Algorithm

Datasets	CASIA v1.0		CASIA v2.0	
Proposed Algorithms	CNN + HWT	CNN + DCT	CNN + HWT	CNN + DCT
Accuracy	94.55%	90.9%	96.36%	93.64%
Recall	95.14%	93.2%	97.14%	95.19%
Precision	98.99%	96.96%	99.03%	98%
F-Measure	97.03%	95.04%	98.08%	96.57%

VI. Conclusion

Image splicing is a common technique employed for image forgery, where a forger copies and pastes parts of one image into another to create a tampered image. This paper presents a robust algorithm for detecting image-splicing forgery by leveraging a deep learning-based approach integrated with Haar Wavelet Transform (HWT). The algorithm employs Convolutional Neural Networks (CNN) to automatically extract features from color images, and HWT is applied to enhance the feature representation. The final feature set is used by a Support Vector Machine (SVM) for classification. Comprehensive experiments were conducted to evaluate the performance of the proposed algorithm on two standard tampered image datasets: CASIA v1.0 and CASIA v2.0. The results demonstrate that the proposed algorithm outperforms recent methods in terms of accuracy, precision, and True Positive Rate (TPR). Notably, the proposed method achieves a high detection accuracy of 94.55% and 96.36% on CASIA v1.0 and CASIA v2.0, respectively.To further analyze the robustness of the proposed algorithm, additional experiments were conducted by replacing HWT with Discrete Cosine Transform (DCT) followed by Principal Component Analysis (PCA). While the DCT-based approach achieved reasonable performance, the HWT-based algorithm demonstrated superior accuracy and precision, highlighting its effectiveness in capturing both spatial and frequency domain features. Moreover, the algorithm benefits from a low-dimensional feature vector, making it computationally efficient and suitable for real-world applications.

Future work should focus on extending the proposed approach to not only detect forgery but also localize the regions of tampering in spliced images. This enhancement would provide valuable insights into the nature and extent of forgeries, further advancing the capabilities of image-splicing detection systems.

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