

# Optimizing Robustness and Invisibility in Digital Image Watermarking: A SVM-Based Multi-Level DWT and SVD Approach

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**Abstract**— This research introduces a new digital image watermarking approach that utilizes discrete wave transformation (DWT), Support vector machine, and singular value decomposition. The method improves robustness under various assault situations by using the SVM classifier during watermark extraction. Multi-level DWT splits the host picture into sub-bands when embedding, and the coefficients are used as input for SVM. After SVD, the scaling factor embeds the watermark. Comparing the proposed approach to existing research under various attacks, the experimental findings demonstrate that it strikes an equilibrium between robustness and invisibility for watermarks of varying sizes. Support Vector Machine is a contemporary category of machine learning techniques that is extensively employed for the purpose of solving classification problems.

**Keywords**- Bit Error Rate (BER), Discrete Wave Transformation (DWT), Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE). Singular Value Decomposition (SVD), Support Vector Machine (SVM).

## I. INTRODUCTION

### A-Discrete Wave Transformation:

DWT has several scientific and technological uses. It makes watermarking more resistant to image processing and more energy-efficient. DWT was widely employed for various reasons due to its spatiotemporal feature [1]. DWT splits the host image into LH, HL, HH, and LL sub-bands. The information from the host picture is shifted to the LL sub-band after the first stage of DWT. The wavelet technique allows decomposition till the sub-bands meet the watermark size. After passing through Low-Pass & High-Pass filters, each DWT decomposition breaks into four bands. Bands show whether filters are applied to rows or columns [2]. According to Figure .1 any image will be decomposed in LL1, LH1, HL1, and HH1 then again LL1 outperforms the other sub-bands in compression attacks, according to LL2, HL2, LH2, HH2) similar as LL3,LH3,HL3,HH3.. This makes the LL sub-band ideal for safe watermarking.

These filters are used to process a signal from a specific source. These filtering techniques generate two distinct bands, one

containing the approximation of the signal's essential information and the other containing the details of the signal at a higher frequency. It is the inverse of what was done to reverse the procedure and bring back the original signal. The filter bank method uses a combination of a low-pass and a high-pass filter to reduce noise [3].

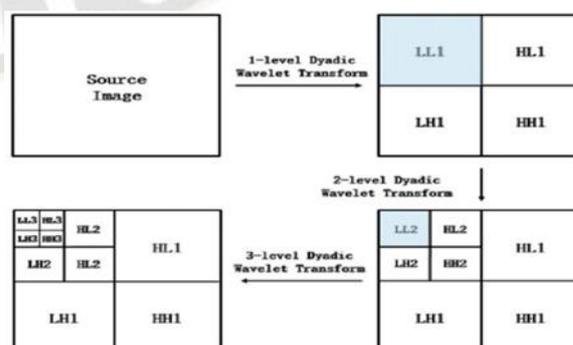


Figure.1

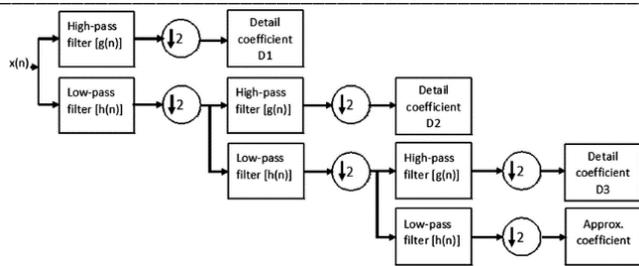


Figure.2

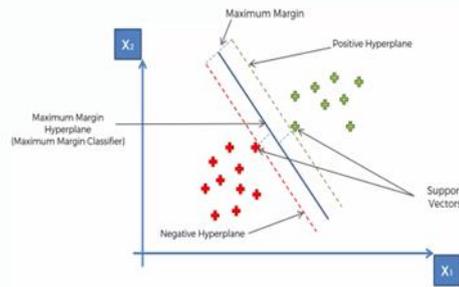


Figure.3

**B-Singular Value Decomposition:**

The SVD approach is a more well-known technique that has found use in many different areas of study, including watermarking, image processing, PCA, and crypto.

Let us assume  $A_{m \times n}$  Matrix. Matrix A decomposed into three Matrix [4,5].

$$A = U \Sigma V^T \quad (1)$$

Matrix U and V are Orthogonal Matrix.

$\Sigma \rightarrow$  Diagonal Matrix

Singular values are  $\sigma_1 \geq \sigma_2 \dots \rightarrow \sigma_r$

$r \rightarrow$  Rank of Matrix A.

$V_{n \times n}$  {V contains eigen vector of

$A^T A$  (V is orthogonal)}

$\Sigma_{m \times n}$  { $\Sigma$  contains eigen vector of

$\sqrt{A^T A}$  ( $\Sigma$  in diagonal)}

$U_{m \times m}$  {U Contains eigen vectors of  $AA^T$ }

Here we will find out Eigen Vector and Eigen Values[6].

$$A = U \Sigma V^T$$

$$A = U \Sigma V^T \quad (2)$$

**C-Support Vector Machine:**

Invoking the Support Vector Machine (SVM) training procedure, decision function will be identifying a hyperplane with a maximum Margin between the support vectors of both class labels [7,8].

$$\text{Margin (Mr} = D^- + D^+). \quad (3)$$

A Hyperplane or Control line for Cooperation of two Different Class having different Data

The main problem in Linear SVM is the complexity range that will depend on the number of features used. In the case of two characteristics, the hyperplane merely parallels the line, whereas, in the case of three features, the hyperplane merely parallels the plane.

**II. PROPOSED METHOD**

**A-Watermark Embedding Algorithms:**

A detailed algorithm for watermark embedding with DWT, SVD, and SVM is provided below:

- 1- Import the watermark and host image into the application.
- 2- The host image should be pre-processed by converting it to a grayscale image and resizing it to 512x512 pixels..
- 3- The watermark image should undergo pre-processing by being transformed into a grayscale image and resized to a dimension of 144x144 pixels.
- 4- Use DWT to divide the host image into four sub bands: LL, LH, HL, and HH.
- 5- Embed the watermark in the DWT decomposition's LL sub-band.
- 6- Perform Singular Value Decomposition (SVD) on the LL sub-band to obtain its singular values and singular vectors.
- 7- Choose the largest singular values and their corresponding singular vectors as the features to be embedded with the watermark.
- 8- Train a Support Vector Machine (SVM) classifier with the chosen singular values and vectors as the feature space.
- 9- Embed the watermark into the chosen LL sub-band using the developed SVM classifier.
- 10- To obtain the watermarked picture, use Inverse DWT (IDWT) on the four sub-bands.
- 11- Save the watermarked image for further analysis and evaluation.
- 12- Measure PSNR and correlation coefficient to evaluate watermarked images.

**B-Watermark Extraction Algorithms:**

Algorithm for watermark extraction using DWT, SVD, and SVM:

- 1- Pre-processing: Load the watermarked and original SVM classifier picture.
- 2- Apply DWT to the watermarked picture to obtain the sub-bands.
- 3- Apply SVD to the LL sub-band to retrieve the singular values and singular vectors.
- 4- Watermark Extraction: Extract the watermark from the singular values by subtracting the values proportional to the original image.
- 5- Inverse Singular Value Decomposition: Get the watermarked LL sub-band with the inverse SVM.
- 6- To obtain the watermarked image, use the inverse Discrete Wavelet Transform.
- 7- Use the SVM classifier you've trained to decide if the watermarked image is authentic or counterfeit.
- 8- Compare the watermark you retrieved to the original watermark image to ensure accuracy.
- 9- Post-processing: Evaluate the results of the watermark extraction process and determine the accuracy and robustness of the watermark.

The specifics of the DWT, SVD, and SVM methods used [2], as well as the parameters and techniques for extracting the watermark, will affect the performance and robustness of the watermark extraction system.

**C-Extraction of watermarks with a trained and tested support vector machine**

RW- Reference of Watermark.  
SW- Signature of Watermark.

SVM training uses the optimal feature vector set. The SVM receives statistically significant features and DWT coefficients. The dataset consists of 1024 blocks, which are divided into two distinct sets. The initial 512 blocks are for the training pattern and the remaining blocks are for the testing pattern. Fig. 4 shows this process. Classified testing patterns create the signature watermark (SW). To locate the signature watermark (SW), trained SVM classifies testing patterns. SVM training uses the reference watermark RW (512 bits), while SVM testing uses SW (16 \* 32) binary image.

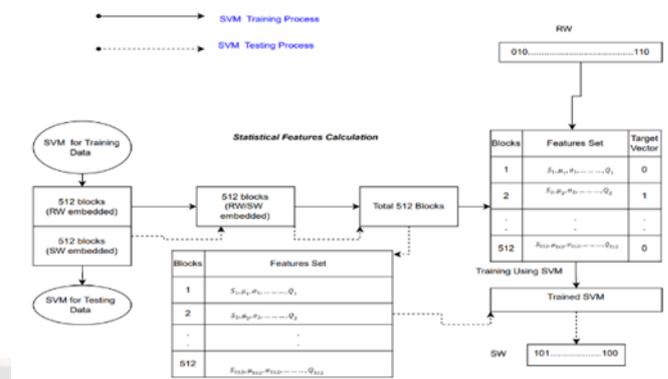


Figure.4 Watermark extraction SVM training and testing Model

**III. RESULTS & DISCUSSION**

The suggested solution is applicable to host pictures of 512 \* 512 pixels and Watermark images of 144 \* 144 pixels. To validate the recommended Digital Watermarking Using SVD and DWT, many samples are employed. The DWT and SVD breakdowns are used [9,10]. PSNR denotes imperceptibility, whereas correlation coefficients denote robustness.

**PSNR:**

The PSNR value, represented as is used to calculate the image's quality by Equation(4).

$$PSNR=10\log \{(255)^2/MSE\} \quad (4)$$

**MSE:**

Where Mean Square Error is computed by this Formula by equation (5).

$$MSE = \frac{1}{N N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} [f'(x, y) - f(x, y)]^2 \quad (5)$$

where  $N \times N$  Represents the image size,  $f'$  represents the reconstructed image, and  $f$  represents the original image Pearson's Correlation Coefficient formula is used to calculate the robustness of the retrieved watermark against various attacks by equation (6)

**Which is stated as PCC (Pearson's Correlation Coefficient)**

$$PCC = \frac{N \sum(x,y) - (\sum x \sum y)}{\sqrt{[N \sum x^2 - (\sum x)^2] [N \sum y^2 - (\sum y)^2]}} \quad (6)$$

In the above Method x,y variables are original and Extracted watermark.

**Bit Error Rate (BER)**

$$BER = \frac{1}{N N} \sum_x \sum_y [f'(x, y) * f(x, y)] * 100\% \quad (7)$$

Where  $f(x,y)$  and  $f(x,y)$  is Recovered and the Original watermark size is  $N \times N$ .

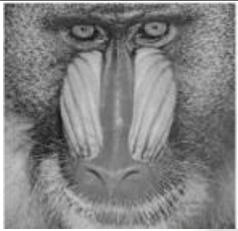
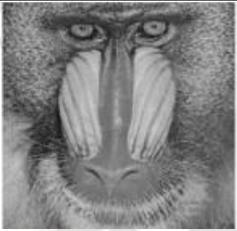
**A-Imperceptibility:**

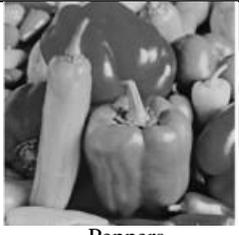
Different image databases have tested the imperceptibility of the suggested system. PSNR (dB) measures imperceptibility between host and watermarked images [9,11,12,13]. Table.1 shows the watermarked image with PSNR, NC, BER and retrieved watermark under no attack. Similar way we find out the PSNR, NC, BER of all Images.

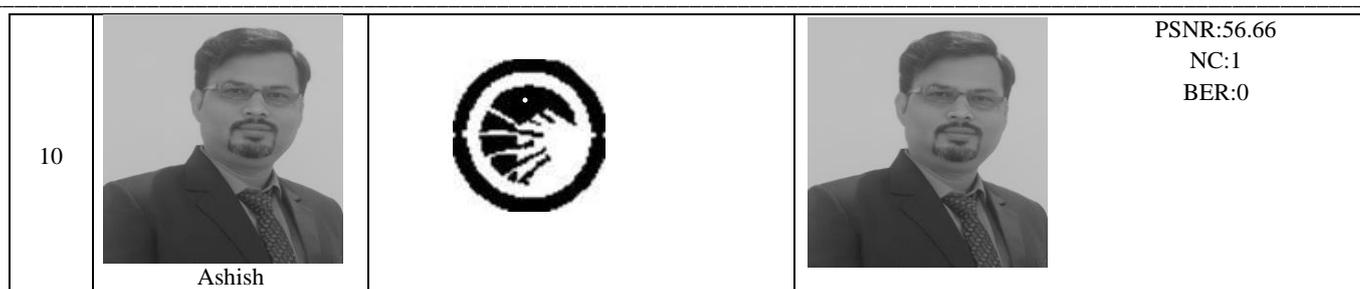
This study examined watermarking scheme assaults. Speckle noise (SN), Gamma Correction (GC), Motion Blur (MB), histogram equalization (HE), image sharpening (IS), JPEG compression with a specific quality factor (JPEG(QF)), cropping (CR), rotation (RT), scaling (SCL), and translation

(TR) were considered Non-Geometrical attacks (NGA and Geometrical Attacks (GA). The robustness of the proposed watermarking method was tested on different types of images to evaluate its performance under these attacks according to Table.2,3,4.

Table .1 Show the Host Images, watermark images, Watermarked images (With PSNR, NC,BER)

S. No	HostImages (512X512)Pixels	Watermark images(Binary Watermark 144x144)Pixels	Watermarked images
1	 Lena		 PSNR: 56.02 NC:1 BER:0
2	 Baboon		 PSNR: 56.13 NC:1 BER:0
3	 Cameraman		 PSNR:56.32 NC:1 BER:0

4	 House			PSNR: 56.15 NC:1 BER:0
5	 Boat			PSNR :56.03 NC:1 BER:0
6	 Man			PSNR: 56.91 NC:1 BER:0
7	 Barbara			PSNR: 56.17 NC:1 BER:0
8	 Peppers			PSNR: 56.33 NC:1 BER:0
9	 Xray			PSNR: 56.25 NC:1 BER:0



In this paper compare NGA in terms of Normalized Correlation of [4] with our proposed Results of the Attack and shows the result in Table.3.

Table .2 Different NGA in terms of NC

Attacks	LENA	MEN
Sharpening	1	1
Speckle noise ( $\sigma = 00.05$ )	0.6774	0.6672
Motion blur (MB)	0.7602	0.7632
Cropping (50%)	0.9799	0.9701
Gamma correction (GC) (0.6)	0.9962	0.9545
JPEG (40)	0.9766	0.9633
JPEG (50)	0.9845	0.9822
JPEG (60)	0.9922	0.9923
JPEG (70)	1	1
Histogram Equalization (HE)	0.985	0.9753

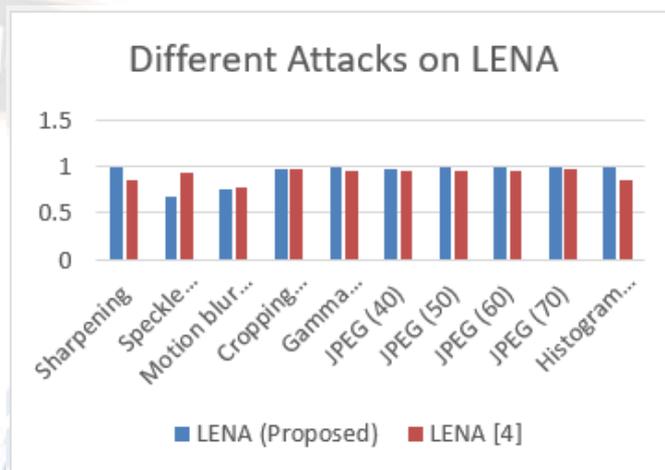


Figure:5 (a) NGA in Terms of NC on LENA

Table .3 Compare Resultant with [4] for Different NGA in terms of NC

Attacks	LENA (Proposed)	Lena [4]	MEN (Proposed)	MEN [4]
Sharpening	1	0.8616	1	0.8689
SN( $\sigma = 0.05$ )	0.6774	0.9384	0.6672	0.9199
Motion blur (MB)	0.7602	0.7682	0.7632	0.7681
Cropping (50%)	0.9799	0.9768	0.9701	0.9695
GC(0.6)	0.9962	0.943	0.9545	0.923
JPEG (40)	0.9766	0.9428	0.9633	0.9374
JPEG (50)	0.9845	0.9461	0.9822	0.9499
JPEG (60)	0.9922	0.9571	0.9923	0.9564
JPEG (70)	1	0.9685	1	0.9629
HE	0.985	0.8472	0.9753	0.8563

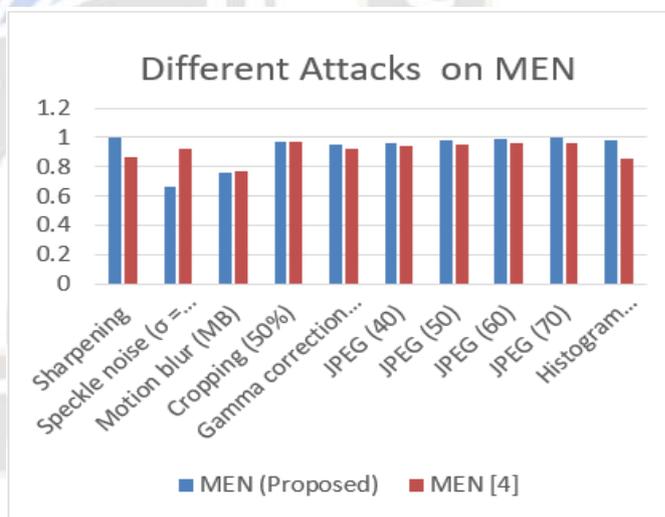


Figure:5 (b) NGA in Terms of NC on MEN

**B- Robustness Against Different Attacks**

Researcher find the Robustness against Different attacks [9,11,12,13,14] by Rotation, Scaling and Translation.

**Rotation:**

Rotation attack is robust from 0° to 90°. Five standard Images demonstrate rotational assault resistance. Performance

diminishes as rotation approaches 45° and increases until 90° according to Table.3. Rotation attacks lose information.

Table .4 Watermark produced through NC for various Rotations Angel (RTA)

	RTA 5°	RTA 15°	RTA 30°	RTA 45°	RTA 90°
<b>Lena</b>	0.9527	0.871	0.826	0.7718	1
<b>House</b>	0.8857	0.8034	0.7936	0.7084	1
<b>Boat</b>	0.9223	0.8637	0.7669	0.7223	1
<b>Man</b>	0.9132	0.779	0.7625	0.6672	1

while 45° rotation loses the most. Our analysis rotates the watermarked image while maintaining image size Figure.6

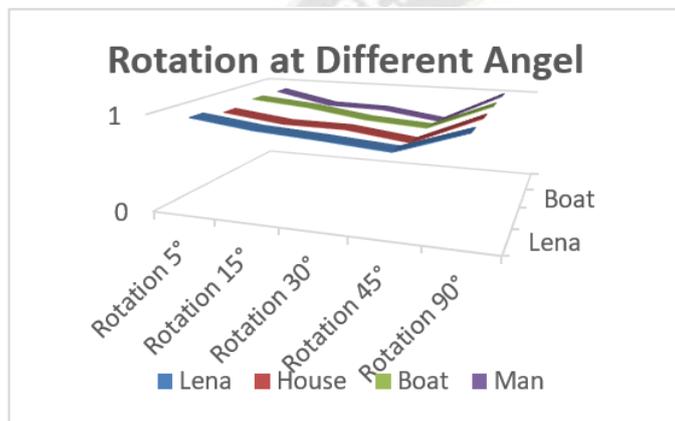


Figure.6 Rotation at Different Angel

**Translation:**

Translation attack performance is also observed. Images with pixel translations from 0 to 75 pixels Representative result: robustness against X-axis translation. The technique works well for translations under 50 pixels. The algorithm resists translation assaults according to Table.5 and Figure 7.

Table .5 Normalized Correlation extracted watermark for different Translation

	Tra (5,5)	Tra (10,10)	Tra (20,20)	Tra (30,30)
<b>Lena</b>	0.986	0.9799	0.9622	0.901
<b>House</b>	0.9424	0.9692	0.9092	0.834
<b>Boat</b>	0.9808	0.9605	0.9122	0.8742
<b>Man</b>	0.975	0.9623	0.8724	0.852

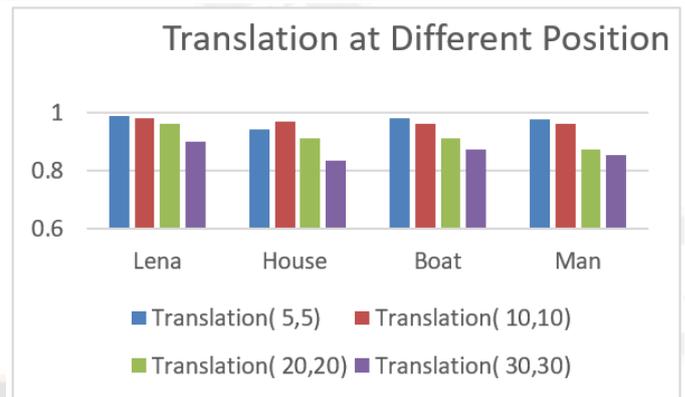


Figure.7 Translation at Different Positions

**Scaling:** Scaling attack performance is also observed. Images with pixel Scaling from 0.6 to 0.76 pixels according to Table.6 and Figure .8 its Representative result.

Table .6 Normalized Correlation extracted watermark for different Scaling

	Scaling (0.6)	Scaling (0.76)
<b>Lena</b>	0.6579	0.9972
<b>House</b>	0.6817	0.9815
<b>Boat</b>	0.4995	0.9510
<b>Man</b>	0.4122	0.9012

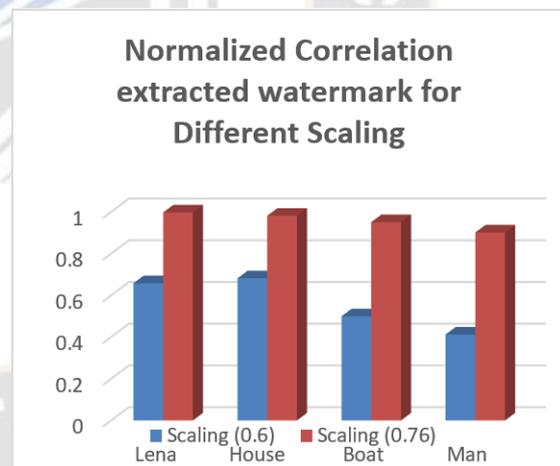


Figure.8 Scaling at (0.6,0.76)

**IV-CONCLUSION**

This research developed a new digital image watermarking method using DWT, SVM, and SVD. Watermark extraction improved attack robustness with the SVM classifier. SVM used coefficients from a multi-level DWT to subdivide the host Picture. The watermark was added through SVD scaling. Different assault strategies were compared to the proposed method. The technique balanced robustness and invisibility for different watermark sizes. SVM was effective for watermark classification. DWT, SVM, and SVD improve digital picture

watermarking. The results suggest that the recommended technology is promising for applications requiring strong and invisible watermarking in the face of various image modifications and attacks. Optimizations and research may improve the process and develop the field.

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