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Steganalysis of Skin Tone Images Using Textural Features

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Abstract*: Around 700 million selfies are posted daily on social media. Skin tone based steganography refers to a steganography method where the confidential message data is incorporated within the skin tone region of images. Skin tone area of an image provides an excellent place for data hiding. The objective of this work is to detect whether any message is hidden in the skin portion of image. Different methods like LSB based, signature based etc. exists for steganalysis of images that concentrates on the entire image. This work focusses on a steganalytic technique based on textural features of skin tone images. The statistics on the texture of human skin acquired from cover and stego images are used for creating a trained classifier model and then tested using three classifiers. Existing tools like StegHide, Outguess etc. use different methods for hiding information in images. Various steganalytic techniques exist to detect messages concealed by means of above tools, which give an accuracy range between 85% and 96%. As the complexity of hiding is increased by embedding in transform domain, the existing detection rate using GLCM is 91.79%. From the experimental results, it is observed that an accuracy of 93% is obtained and the proposed technique outperforms existing methods in terms of detection rates.

***Index Terms*: Skin tone image, Steganalysis, Texture, Gray-level Co-occurrence matrix, Wavelet, Support Vector Machine**

I. INTRODUCTION

In the current digital era, transmission of data in a secure manner is of primary concern. Various techniques have been developed to ensure the security of information being transmitted, one of the techniques being steganography. Steganography is the practice of covert communication employing various digital media such that the transmission of the data remains undetectable [1]. Nowadays people exchange information through internet. Taking photos and posting in social media has been very popular in recent years. In this type of communication there is a threat that people can hide information and share with other people. Due to technological advances, people involved in cybercrime, Cyber terrorists can use Internet as a supplement to regular attacks.

Steganalysis is the process of identifying existence of concealed messages integrated in digital media using any technique of steganography. In the last few decades, many experimental studies have been carried in the field of steganalysis. The objectives of steganalysis are to identify whether or not any hidden information is embedded in a cover media, and if any, estimate the span of concealed message and retrieve the content. Steganalysis has been employed in computer forensics, identifying computer based attacks on nations, tracing online illicit deeds and collecting proof on inquisitions, especially in the case of anti-social elements [5].

In facial images, selfies etc., skin tone region is a promising area for hiding information and remains undetectable to human eye at a glance. This paper introduces an alternative approach to steganalysis of skin tone images based on texture analysis of wavelet bands and SVM classifier. Section II describes about related works in texture based and wavelet based steganalysis. Details of texture analysis and methodology are explained in Section III. Finally, Sections IV and V respectively provide results and conclusions.

II. RELATED WORKS

In the past few years several researches have been carried out in the field of Steganalysis and is still going on. Different approaches to steganalysis include visual detection methods, first order, second order and higher order statistical detection methods, universal detection methods etc. One of the main data hiding techniques in spatial domain is related to LSB steganography and many works have been proposed for steganalysis of LSB steganography methods [2-3].

Specific steganalysis and universal steganalysis are two major steganalysis classifications[4]. In specific steganalysis, the procedures used to reveal the existence of concealed information are targeted on a specific embedding algorithm. The procedures applied in universal steganalysis are not meant for a particular embedding algorithm, but used to detect any steganography content. As details about embedding algorithm are unknown, these methods try to extract information from image statistics. In this type of steganalysis, the main steps are the extraction of features and subsequent classification.

Tao Zhang et.al [2] proposed a new steganalysis technique. Here the steganalysis technique was based on the statistical observations on difference image histograms. This technique was mainly useful for detecting least significant bit steganography.

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The image histogram of the original image and the stego image were generated and difference between the two was computed. The physical quantity, generated from the transition coefficients between difference histograms of these images, could be used to classify stego images from cover images.

Arooj Nissar et.al [4] gave a review about various steganalysis techniques. The author has carried out an investigation on the numerous methods suggested for the image steganalysis and compared the performance of these methods. Jan Kodovský et.al [5] proposed a new method to perform steganalysis. Here steganalysis was done by a classifier called ensemble. Usually support vector machine had used a classifier in predicting stego images and cover images.

In [6], the authors proposed a feature based steganalysis technique to reveal the presence of steganography content hidden using tools NsF5, JPHide & Seek and PQ. The features extracted were used to train the classifiers J48, SMO and Naïve Bayes and their performance on test set in terms of accuracy and speed was analyzed.

In [7], Arooj Nissar et.al proposed a technique of steganalysis, based on the spatial gray dependency technique for texture analysis. The information on the texture obtained from original and stego images were used to train a Neural Network Classifier and later applied on test images.

Rahul Ranjan et.al [8] proposed a method for steganalysis using machine learning approach. Their work was to detect the presence of hidden information, inserted by the steganography tool StegHide, in JPEG images using a Decision Tree classifier. They developed a steganalysis tool that used the Decision Tree classifier to classify the image as either a cover image or stego image.

III. METHODOLOGY

The objective of this work is to detect whether any message is hidden in the skin portion of image. The method proposed comprises of three phases: skin detection, extraction and classification of features. An image is given as input and the region of interest (ROI), which is skin tone, is identified from the image. The skin detected area is cropped and next it is converted into transform domain using DWT. Next step is to extract textural features using GLCM from one of the high frequency bands. The extracted feature vector is used to train three classifiers, viz SVM, LDA and Naïve Bayes classifier. Finally the performance of the classifiers are analyzed.

A. Skin Detection

As the Region of Interest is skin area of an image, the preprocessing step is skin detection. Skin pixels in an image are segregated from non-skin pixels by this process. This is a challenging task as human skin color varies for people from region to region. The HSV (Hue, Saturation, and Value) model is used to perform skin tone detection on the input image.

In this work, skin tone detection is done using HSV model. Any RGB color image can be altered to HSV color space using the given equations [1-3].

$$H = \begin{Bmatrix} h, B \le G \\ 2\pi - h \end{Bmatrix} \quad (1)$$

where $h = \cos^{-1} \dfrac{\frac{1}{2(R-G)} + (R-B)}{\sqrt{\left((R-G)2 + (R-G)(G-B)\right)}}$

$$S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} \quad (2)$$

$$V = \max(R,G,B) \quad (3)$$

In the HSV color model, threshold values for human skin tone lies in the range sat_min=0.23, sat_max=0.68, hue_min=0 degree and hue_max=50 degrees.

B. Feature Extraction

Moreover in the subsequent phase, wavelet decomposition is carried out on skin cropped area of the image. The wavelet transform decomposes an image into a set of basis functions called ‘wavelets’ and provide the time and frequency information simultaneously (Davidson et.al 2013). Here Haar wavelet is used where each image is divided into four bands. Fig. 1 shows the 2-D DWT of an image.

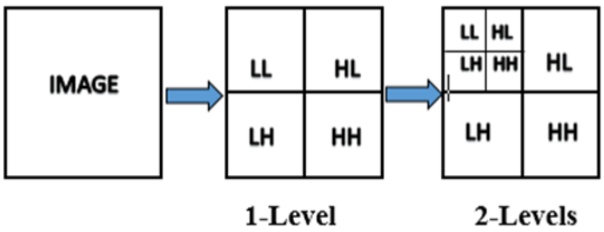

Fig. 1 2-D Discrete Wavelet Transform

In the proposed work, we explain about extracting textural features of images using GLCM method. So, we select one of the high frequency sub bands, compute Gray-Level Co-occurrence Matrix of the selected region, extract textural features from it and then use these features for classification.

C. Gray Level Co-occurrence Matrix (GLCM)

Texture of an image provides information about the spatial ordering of intensities in an image. Gray Level Co-occurrence Matrix (GLCM) is a significant second order statistical method to conduct texture analysis. The GLCM computes how frequently distinct intensity level combinations coexist in an image [9][11].

A GLCM is a matrix that contains row count and column count equivalent to the count of intensity levels, L in the image [12]. Each matrix component P (i, j | Δx, Δy) refers to the relative frequency between two pixels located within a specified area such that one pixel is of gray level i and the other of gray level j, separated by a pixel distance (Δx, Δy) [12] [17]. Consider an image *I* of size *R x S* pixels with *L* intensity values.

The co-occurrence matrix is

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defined as:

$$P(i, j / \Delta x, \Delta y) = WQ(i, j / \Delta x, \Delta y) \quad (4)$$

where

$$W = \frac{1}{(R - \Delta x)(S - \Delta y)} \quad (5)$$

$$Q(i, j / \Delta x, \Delta y) = \sum_{s=1}^{S-\Delta y} \sum_{r=1}^{R-\Delta x} A \quad (6)$$

and

$$A = \begin{cases} 1 \text{ if } f(r,s) = i \text{ and } f(r+\Delta x, s+\Delta y) = j \\ 0 \text{ otherwise} \end{cases} \quad (7)$$

It can also be computed as component P(i, j | d, θ) of matrix on the basis of two quantities, *d and* θ. 'd' refers to relative distance between the pixel pair and θ refers to relative orientation angle. Figure 2 illustrates computation of a co-occurrence matrix with (d=1, θ= 0^0) for an image segment of 4 x 4 with four gray levels:

The normalized co-occurrence matrix is computed by dividing the entire matrix by sum of all elements of co-occurrence frequency matrix. Haralick et.al [9] suggested fourteen textural characteristics which could be computed from the GLCM.

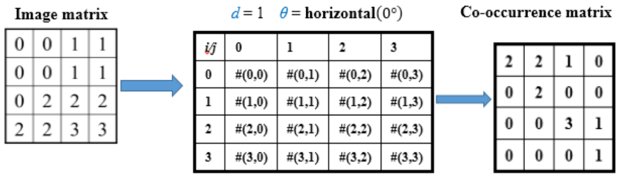

Fig 2. Example of GLCM

In this work, value of quantized gray levels in co-occurrence matrix is taken as 8. Two GLCMs are calculated, one with displacement=2 and orientation in the horizontal direction i.e. d=2, θ=0^0 and second one with displacement=2 and orientation in the vertical direction; i.e. d=2, θ=90^0. For this work, twenty two textural features are calculated from these co-occurrence matrices and applied for the classification of images. The 22 textural features used are listed Table I.

Table I. Textural features used in the proposed scheme

Attribute #	Name of Attribute
F1	Autocorrelation
F2	Contrast
F3	Correlation
F4	Cluster Prominence
F5	Cluster Shade
F6	Dissimilarity
F7	Energy
F8	Entropy
F9	Homogeneity
F10	Homogeneity
F11	Maximum probability
F12	Sum of squares: Variance
F13	Sum average
F14	Sum variance
F15	Sum entropy
F16	Difference variance
F17	Difference entropy
F18	Information measure of correlation1
F19	Information measure of correlation2
F20	Inverse difference
F21	Inverse difference normalized
F22	Inverse difference moment normalized

Equations for Haralick features are given in Table II.

Table II. Haralick features

Textural Features proposed by Haralick [9]	Formula
Angular Second Moment / Energy	$=\sum_i \sum_j p(i,j)^2$
Contrast	$\sum_{n=0}^{L-1} n^2 \{\sum_{i=1}^{L} \sum_{j=1}^{L} p(i,j)\}, \lvert i-j \rvert = n$
Correlation	$\frac{\sum_i \sum_j (i j) p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$
Variance	$= \sum_i \sum_j (i-\mu)^2 p(i,j)$
Inverse Difference Moment	$= \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$
Sum Average	$= \sum_{i=2}^{2L} i\, p_{x+y}(i)$
Sum Variance	$= \sum_{i=2}^{2L} (i-f_8)^2 p_{x+y}(i)$
Sum Entropy	$f_8 = -\sum_{i=2}^{2L} p_{x+y}(i) \log\{p_{x+y}(i)\}$
Entropy	$= -\sum_i \sum_j p(i,j) \log(p(i,j))$
Difference Variance	= variance of p_{x-y}
Difference Entropy	$= -\sum_{i=0}^{L-1} p_{x-y}(i) \log\{p_{x-y}(i)\}$
Maximal Correlation Coefficient	=(second largest eigenvalue of Q)$^{1/2}$ where Q(i,j)= $\sum_k \frac{p(i,k)p(j,k)}{p_x(i)p_y(k)}$

For each image, the GLCM in two different orientations (horizontal and vertical) was computed and 22 textural features were obtained from each GLCM resulting in a total of 44 features. Finally the feature vector will be a vector of order 1 x 44 for an image.

D. Classification

In this work, three classifiers viz, SVM, naïve Bayes and LDA are used for classification. The feature vector obtained from the co-occurrence matrix is given as input to the classifiers.

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The three classifiers are trained in the training phase with the texture related feature sets. In the testing phase, a stego image is distinguished from a non-stego image using the trained classifiers. The performance of the three classifiers are also compared and analyzed. The image database is divided into training dataset and testing dataset. The following steps are carried out next.

E. Proposed Algorithm

Step 1. Choose an image from the database.
Step 2. Detect skin area of the chosen image and crop it.
Step 3. Perform wavelet decomposition using Haar wavelet on the skin area, where each image is subdivided into four sub bands.
Step 4. Select one of the high frequency sub bands and extract features using GLCM method.
Step 5. Select a classifier. In the training phase, the features obtained from the image are used to train the classifier.
Step 6. Steps 1 to 4 are repeated for all the images in testing data set. The trained classifier is applied so that the unseen image is classified as stego or non-stego image.
Step 7. Analyze the performance of each classifier using various parameters.
Step 8. Stop.

The above process is repeated to obtain stego images from cover images and form the training set.

Figure 3 illustrates the overall process of the proposed scheme.

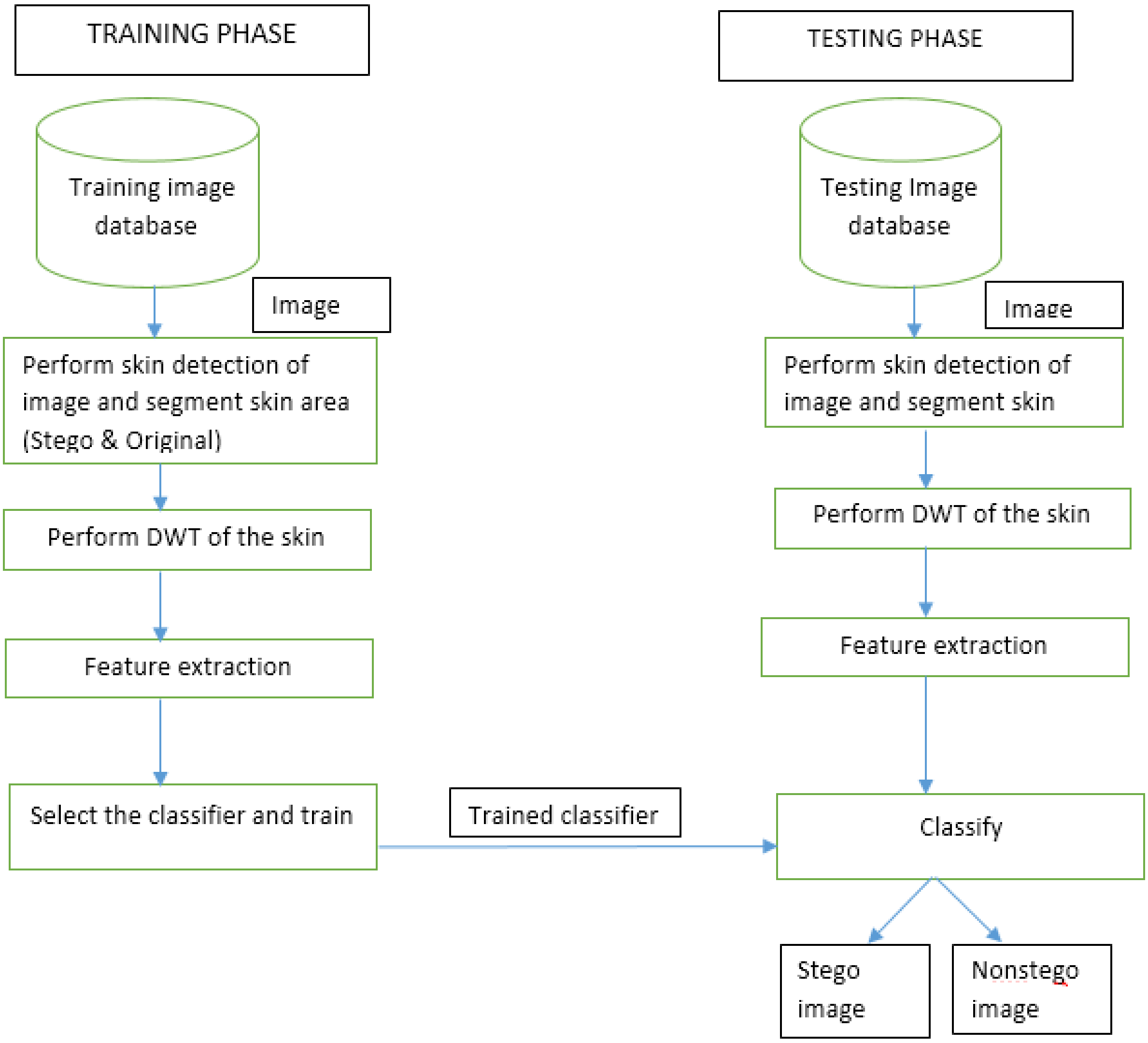

Fig. 3 Framework of Proposed Steganalysis Scheme

IV. RESULTS AND DISCUSSIONS

The proposed work was implemented using Matlab. An image database was constructed for the work. Images were downloaded from the Internet, publicly available websites [21][22]. Several images of individuals belonging to different regions and races were included in the database. Training data and testing data were setup from this database. During the training phase, 300 images were applied and 176 images were applied in the test phase. The training dataset consisted of 300 images where stego images and cover images were 182 and 182 respectively. The stego images were created from the cover images by embedding information in the skin tone region using DWT hiding techniques.

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Table III and Table IV shows a sample of value of feature vectors obtained for non-stego and corresponding stego images in the training data set respectively.

Table III. Feature Vector for Non-stego images

	Feature Vector Values									
Non-stego images	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7	…	Feature 21	Feature 22
NS 1	7.096466	662.7792	2.287243	13.45193	7.203614	667.9514	2.261753	…	12.57027	0.830061
NS 2	7.379192	582.5901	2.525447	14.40532	7.589409	633.5811	2.500699	…	14.00586	0.812912
NS 3	7.152796	689.8702	2.296472	13.76983	7.534909	771.3242	2.218966	…	12.66108	0.835399
NS 4	7.721562	597.3422	2.659798	15.14566	7.733777	592.1704	2.660415	…	15.03917	0.801672
NS 5	8.111488	629.2486	2.685338	15.67703	7.96431	592.1952	2.727882	…	15.6312	0.797874
NS 6	11.07688	770.6395	3.365575	21.75248	11.50868	824.4972	3.226799	…	20.18015	0.770782
NS 7	6.222794	583.76	2.123203	11.88765	6.258819	580.7534	2.119936	…	11.4072	0.838548
NS 8	8.994523	787.193	2.688631	16.87889	9.058593	795.2485	2.66825	…	15.67507	0.804663
NS 9	5.278163	458.8859	1.872857	10.00751	5.229167	435.22	1.899397	…	9.661321	0.852224
NS 10	4.959064	409.0549	1.816682	9.438873	4.960374	397.1518	1.828279	…	9.11925	0.856699
								…		
STD (Standard Deviation)	1.693265	114.474	0.43453	3.371264	1.789212	135.6448	0.4059	…	3.103327	0.025692

Table IV. Feature Vector for Stego images

	Feature Vector Values									
Stego Images	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7	…	Feature 21	Feature 22
S1	5.278163	458.8859	1.872857	10.00751	20.11052	9.544286	0.854355	…	5.229167	0.034721
S2	4.959064	409.0549	1.816682	9.438873	18.79795	9.058418	0.857579	…	4.960374	0.032579
S3	5.107515	419.4524	1.933415	9.968098	19.57407	9.810416	0.849334	…	5.123075	0.009181
S4	4.913279	416.0902	1.763285	9.257179	18.60703	8.770932	0.86172	…	4.914243	0.048519
S5	7.531958	635.8025	2.443657	14.43487	29.52436	13.84553	0.817919	…	7.609066	0.044573
S6	6.866012	630.3021	2.230992	12.99204	26.69483	12.35909	0.832192	…	7.052118	0.069992
S7	7.121315	600.1645	2.486638	14.2307	28.81395	14.24549	0.81568	…	7.29156	0.024215

S8	6.638027	646.2589	2.197222	12.77321	26.37939	12.40067	0.836021	…	6.97265	0.10063
S9	7.329353	742.2854	2.237866	13.57747	28.46099	12.56741	0.832628	…	7.399903	0.1031
S10	6.589996	661.8526	2.161109	12.62476	26.17248	12.15706	0.838466	…	6.769074	0.084075
								…		
STD (Standard Deviation)	3.757765	36.02877	2.176136	5.194504	7.428533	5.089047	1.365305	…	3.783497	0.360727

A. Metrics for Evaluating Classifier Performance

This section describes the parameters used to assess a class ification model's performance. A confusion matrix is a table that tabulates the number of test samples correctly and incorrectly classified by the model. Figure 4 shows the confusion matrix for a binary classifier. Here, the class of interest (i.e. stego image) is called the positive class and the cover image (i.e. non-stego image) is the negative class.

		Predicted Class	
		Cover	**Stego**
Actual Class	**Cover**	True Negatives (TN)	False Positives (FP)
	Stego	False Negatives (FN)	True Positives (TP)

Fig 4. Confusion Matrix

The terms associated with the confusion matrix are given below.

- **True Positives (TP)** denote number of correct classifications of positive class (i.e. stego images that were correctly classified as stego by the model).
- **False Negatives (FN)** denote number of incorrect classifications of positive class (i.e. stego images that were wrongly classified as non-stego).
- **True Negatives (TN)** denote number of correct classifications of negative class (i.e. non-stego images that were correctly classified as non-stego).
- **False Positives (FP)** denote number of incorrect classifications of negative class (i.e. non-stego images that were wrongly classified as stego).

Tables V, VI and VII show the confusion matrix for SVM, Naïve Bayes and LDA classifiers respectively.

Table V. Confusion Matrix of SVM classifier

No of Test images = 176	**SVM Classifier**		
	Predict Cover	**Predict Stego**	**No of Inputs**
Actual Cover	**TN=78**	**FP=6**	**84**
Actual Stego	**FN=6**	**TP=86**	**92**
Total	**84**	**92**	**176**

Table VI. Confusion Matrix of Naïve Bayes classifier

No of Test images=176	**Naïve Bayes Classifier**		
	Predict Cover	**Predict Stego**	**No of Inputs**
Actual Cover	**TN=63**	**FP=21**	**84**
Actual Stego	**FN=17**	**TP=75**	**92**
Total	**80**	**96**	**176**

Table VII. Confusion Matrix of LDA classifier

No of Test images=176	**LDA Classifier**		
	Predict Cover	**Predict Stego**	**No of Inputs**
Actual Cover	**TN=45**	**FP=39**	**84**
Actual Stego	**FN=40**	**TP=52**	**92**
Total	**85**	**91**	**176**

The performance of three classifiers are analyzed using the metrics listed in Table VIII.

Table VIII. Performance Evaluation Measures

Measure	**Formula**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity/Recall/True positive Rate	$\frac{TP}{TP+FN}$
Specificity/True Negative Rate	$\frac{TN}{TN+FP}$
Precision	$\frac{TP}{TP+FP}$
False Positive Rate	$\frac{FP}{TN+FP}$

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Table IX illustrates the performance analysis of the three classifiers to distinguish test image as stego or non-stego. Comparing the values for sensitivity, specificity and accuracy, SVM gave the best performance among the three classifiers with an accuracy of 93%.

Table IX. Performance Analysis of Classifiers

Classifier	FPR	Sensitivity	Specificity	Accuracy
SVM	0.0652	0.9348	0.9286	0.93
Navies Bayes	0.1848	0.8152	0.75	0.78
LDA	0.4348	0.5652	0.5357	0.55

Figure 5 illustrates the graphical representation of the values of performance metrics attained when the three classifiers viz, SVM, Naïve Bayes, and LDA were used for classifying test images.

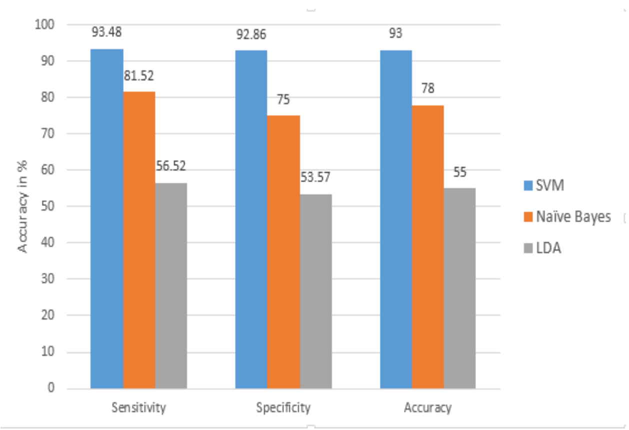

Figure 5. Graphical Representation of performance metrics of three classifiers

Figure 6 shows the ROC to analyze the performance of the three classifiers. It can be concluded from the figure that SVM classifier outperforms other two classifiers.

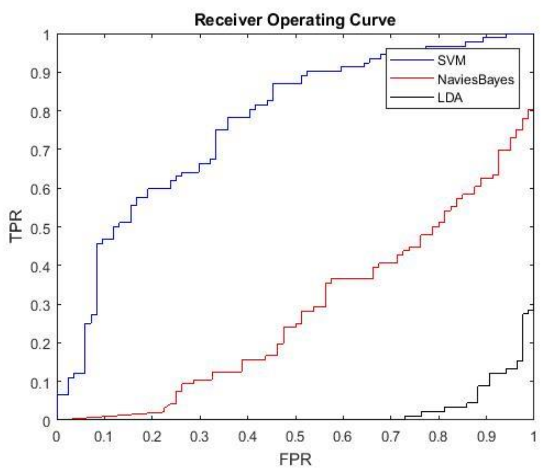

Figure 6. ROC of three classifiers

Table X shows the comparison of the suggested work with prevailing methods based on feature based steganalysis. The comparison makes it clear that the method proposed surpasses the previous methods regarding detection rates.

Table X. Comparison of feature based steganalysis

Existing Work	Methodology/ Classifier Used	Accuracy
Shaohui *et al* (2004)	GGD + Neural Network	83 %
Borah *et al* (2006)	Statistical Textural features + Neural Network(LVQ)	80%
Sedighe *et al* (2012)	GLCM + Neural Network	80%
Arooj *et al* (2013)	GLCM + Neural Network	91.79%
Veenu *et al* (2014)	Markov, Spam, NJD, Run length Features + Ensemble	89.5%
Indradip *et al* (2014)	7th order Central moments, Zernike moments, Invariant Moments + SVM	91%
Desai *et al* (2016)	DCT-BSM and 15-D features + SVM	90%
Proposed Work	**DWT + 22 features of GLCM + SVM**	**93%**

V. CONCLUSION

This paper presents an efficient approach for the steganalysis of skin tone areas of images based on textural features extracted from GLCM. In this work, first the skin tone region is segmented from the image. Next the segmented skin area is converted into transform domain using DWT.

Further, we extract textural features using GLCM from one of the frequency sub bands. Two GLCMs were created and twenty two features were extracted from each GLCM. Thus a feature vector consisting of forty four features was used to train classifiers to distinguish a stego image from a cover image. Three classifiers viz; SVM, Naïve Bayes and LDA were trained and their performance were analyzed on a test set consisting of 176 images. Among the three, SVM gave the best detection rate of 93%. From the comparison of the result with other existing texture based analysis techniques, the proposed method shows better results. Our future work is to test the proposed method on skin tone regions of an image partitioned into blocks.

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