International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

June 2022	Issue 51	Volume 14	Number 2	Pages 322-329

EXPLORATION OF DIGITAL IMAGE TAMPERING USING ENHANCED FEATURE EXTRACTION ALGORITHMS IN MACHINE LEARNING

D. Umamaheswari [1*] E. Karthikeyan [2]

1. Department of Computer Applications, Nallamuthu Gounder Mahalingam College, Pollachi, India
rschlrumamahes@outlook.com
2. Department of Computer Science, Government Arts College, Udumalpet, India, drE.karthi@outlook.com

Abstract- The manipulation of real-world snapshot using software applications or android application before sharing the transformed image on social media is easier. To identify the manipulated part of an image there are some automatic tools that are used to identify the inherent variance between trustworthy images and tampered images. In this work, existing feature extraction algorithms such as Local Binary Pattern (LBP) and Speeded Up Robust Features (SURF), proposed algorithms like Enhanced Local Binary Pattern (ELBP), Enhanced Speeded Up Robust Features (ESURF) are outsourced. The techniques revealed above are compared and also used to extract the exact part that has been tampered in the given set of images. These Feature Extraction Algorithms offer a unique perspective on how to circumvent numerous assumptions about tampering clues in diverse altered image datasets. In the proposed work, it is demonstrated that the ESURF approximates or even beats the above-mentioned proposed methods in terms of consistency, uniqueness, and durability. In addition, compared to previous methods, it can be computed and compared much faster. When paired with PSO, the feature extraction method successfully finds the relevant aspects of the data set, resulting in improved detection performance and accuracy.

Keywords: Feature Extraction, Particle Swarm Optimization, Local Binary Pattern, Speeded Up Robust Features.

1. INTRODUCTION

The machine learning succeeds in all the applications, both the public and private sectors concentrate more on machine learning algorithms due to the accurate results and appropriate detections. Target detection is classified into feature extraction and feature classification. It combines classification algorithm with the detection algorithm for obtaining the expected results [1]. In the area of Image classification and recognition also, the machine learning provides the accurate results. Everything is automated and widely applied in Machine learning. The scope of Improvement and Data handling efficiency is very high in Machine learning.

Pattern Identification is very easily done with the assistance of Machine learning. It provides good classification accuracy in handling images. Machine learning is able to manage multi-dimensional and multi-variety datasets. Detection can also be done with the aide of localization. These algorithms also help us to find out the percentage of tampering in the extracted regions. The major contribution of this work is summarized as follows:

- Existing Feature extraction Algorithms such as LBP and Surf is applied to the tampered images to extract the required features.
- Enhanced Algorithms like ELBP and ESURF is applied to the same images to extort the significant features.
- PSO is combined with all four algorithms to optimize the performance of them.
- The performances of these algorithms are evaluated by applying three different classifiers namely SVM, BPNN and Ensemble.

2. BACKGROUND STUDY

More and more companies incorporate the latest techniques in their workforce. The significant advantage of this incorporating technique is flexibility and speed. Image processing is nowadays less complicated due to the speed of data analysis and high efficiency of image processing techniques. In the field of computer vision, detecting image manipulation is still a big problem [2]. It's because present solutions work well in controlled environments but seems to fail when dealing with actual data.

There are many methods in tampering detection and classification, but feature extraction plays the best. LBP extracts the feature vectors in histograms for every individual image. So that the classifiers can be trained directly using these features vectors [3]. SURF features provide good speed and robustness. It detects the object's rotation, scale and translation. It constructs object models and has its own solidity for grouping points [4]. The feature extraction algorithms when combined with PSO are more effective and give best result than the other. These algorithms act as a best tool selecting an extracting the significant features.

The features were optimized and by employing PSO with the specified feature extraction algorithms and results in good classification accuracy. The PSO algorithm is applicable for solving both minimization and maximization problems. The performance of PSO is accepted well even under pre-processing and post-processing attacks [5].

The classification plays a main role in enhancing the grouping of input images and evaluating the performance. Each classification algorithm has its own significance. It definitely varies from each and every appliance [6]. Detection and classification can be done using Support Vector Machine. The quantity of features is often used to evaluate the classifier's performance. The performance of the system is improved by integrating the decisions in ensemble classification. Due to the inherent characteristics of the ensemble, many researches are conducted using ensemble. Optimum initialization and efficient process are the abilities of BPNN. BPNN provides higher accuracy and superior image quality when compared with other methods.

3. PROPOSED METHODOLOGY

- Feature Extraction: This is the primary step which extracts the features using LBP, ELBP, SURF and ESURF feature extraction algorithms.
- Optimized Feature Extraction: Only most significant features are extracted using PSO_LBP, PSO_ELBP, PSO_SURF and PSO_ESURF algorithms. Figure 1 provides the purposed workflow model.

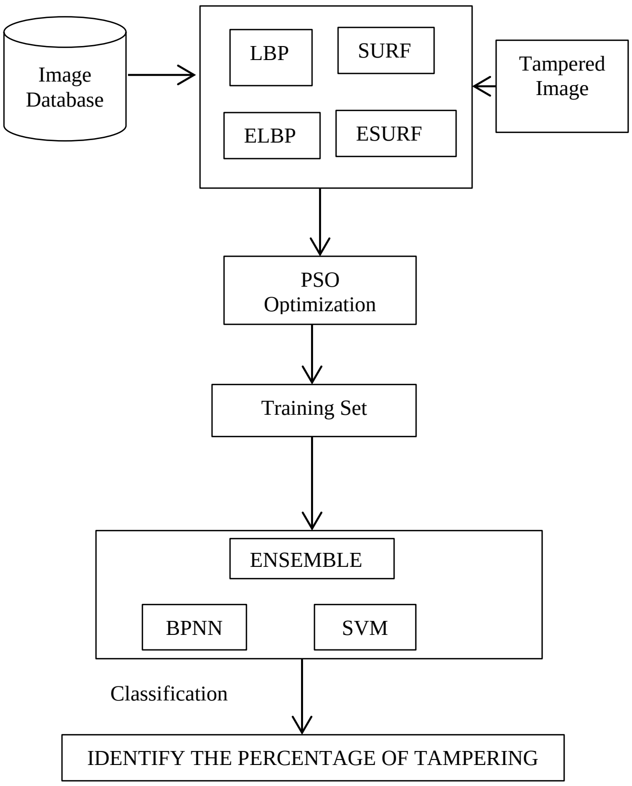

Figure 1. Proposed workflow model

- Classification: In this step, Support Vector Machine, Ensemble and Back Propagation Neural Network are used to classify and assess the performance of Feature Extraction Algorithms.

3.1. Feature Extraction

Representing the resourceful information which helps in image analysis or image classification by establishing a collection of image features is known as Feature Extraction. This technique sometimes provides new features when more than one existing feature is combined. The new features will have new values. It also helps to decrease the redundant data in the image. It increases the precision of the models by extracting more features from the images [7]. Because of the minimized redundant data, training speed is improved and data dimensionality is lowered. Since Feature Extraction plays an essential position in Image Analysis and Classification, applying the correct feature extraction technique should be done with utmost care. The detection of the tampering area is also pointed out after extracting the features [8].

3.1.1. Local Binary Pattern

LBP is a known texture description operator to quantify and extort the local texture information from the various images. Low estimating complication, suitable multi-scale expansion and flat gray-scale changes due to invariance are the most prominent benefits of LBP. The LBP algorithm is mainly applied to find out the object among others. The LBP uses the falsified image as an input and outputs the feature [10]. The pixel intensity is derived by dividing the central pixel by the eight pixels surrounding it. LBP thresholds each pixel's neighborhood by identifying each pixel in a picture, and the result is a binary integer. If the resemblance of the object is very high, it is indicated by low value. The LBP features always provide successful results in case of false positive reduction. But it is known that efficient results are obtained in all terms when compared with other methods. LBP has a number of difficulties, including the loss of local textural information, a lack of spatial support that makes it difficult to detect large-scale textural features, and noise sensitivity.

Procedure 1. Local Binary Pattern (LBP)

Input: Pre-processed image (P1), co-ordinates of center pixel ($x1$, $y1$) radius R Output: Set of features (f)
Step 1: Load the pre-processed image (pi) Step 2: Select the neighbors of size N around the central pixel C for each pixel p. Step 3: Make a comparison of center value c_v with n_v, the neighbor value. Step 4: if $n_v > c_v$ assign1 else assign2 Step 5: $LBP_{N,R} = (x_1, y_1) = \sum_{i=1}^{8} s(c_v - n_v) * 2$ Step 6: Extract the histogram value. Step 7: Extract the expected features (f).

3.1.2. Enhanced Local Binary Pattern

Using the LBP, pixel strength is achieved by dividing the central pixel by the 8 pixels surrounding it. But LBP is enhanced by calculating the feature values from the set of points apart from the individual points. The *ELBP* handles the LBP issues like detecting large-scale textural structures. It tries to capture the local textural information also. With the support of the core pixel and its surroundings, it also addresses noise and fluctuation difficulties. To construct the feature vector, this *ELBP* takes into account the multiple pixels and different neighborhoods. The comparisons of support vectors are minimized with the help of the *ELBP* operator. As a result, the sparsity enhances and the computational ambiguity decreases [3].

$$ELBP = \sum_{i=1}^{P/2} S\left(C_v, C_{v+(\frac{p}{2})}\right) \times 2^{i-1} + 2^{\left(\frac{p}{2}\right)+1} S\ (n_v - m_v) \quad (1)$$

where, $m_v = \frac{1}{p}\sum_{i=1}^{p} p_i$.

$$S\ (x\ ,\ y) \ = \ \begin{Bmatrix} 0,\ x\ -\ y\ <\ 0 \\ 0,\ x\ -\ y\ <\ 0 \end{Bmatrix} \quad (2)$$

To enhance the performance, the enhanced LBP pulls the image's local information. When a larger image is used as an intake for similarity, it becomes more difficult to cope with the large image since calculation takes longer. To address this problem, the *ELBP* is used to reduce dimensionality without sacrificing important features. This approach is particularly efficient in the real time images where it outperforms LBP and provides the accurate results. This *ELBP* aims to improve the LBP's discriminative power even more. This new method has a good feature extraction result and is very efficient. The proposed technique achieves improved classification accuracy while also having a lower time complexity than the original LBP.

3.1.3. Speeded Up Robust Features

It is also one of the patented feature detector and descriptor which is used to detect the various objects in the images. It is used to compare the images by finding out the similarity invariance. The significant features retrieved from the scale invariance are the interest points of a given tampered image. When compared with other algorithms, SURF is much faster because of its features like using integral images etc.

In SURF, first the interest point should be found using interest point detector and the scale space should be built [11]. Then the orientation of each and every interest point should be found. Finally, the descriptor should be built. Interest point descriptor should be distinctive and robust which is mainly used for matching. Both detector and descriptor should be rapid. SURF reuses the calculations and maintains the robustness to scale illumination change and rotation. High dimension, expensive computation, and low matching accuracy when the rotation angle and viewing angle are too big are some of the drawbacks of the SURF feature descriptor [12]. A better algorithm is proposed to tackle the problems mentioned above.

Procedure 2. Speeded Up Robust Features (SURF)

Input: Pre-processed image (PI).
Output: Set of features

Step 1: Load pre-processed tampered image (PI).
Step 2: Construct the integral image (I).

$$\sum(x, y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i, j)$$

Step 3: Construct hessian matrix.
Step 4: Second order derivatives are now used.
Step 5: Identify the feature points first.
Step 6: Applying non-maximal reduction, precisely detect relevant feature points.
Step 7: Find all of the relevant areas in the image.
Step 8: Determine the feature points' proportionate weights (PW).

$$PW = \frac{\text{no. of identified images w.r.t to point } W}{\text{no.of training images}}$$

Step 9: Extract the features (f) that are expected.

3.1.4. Enhanced Speeded Up Robust Features

The low feature detection problem in SURF is rectified in ESURF approach. This algorithm increases the image contrast to the highest level by detecting a greater number of features. This algorithm combines the feature points into a single feature point to reduce the repeated feature point which is collected because of preprocessing. The overlapped regions are checked for concatenated clusters with all the feature descriptors and then the feature points are optimized.

Procedure 3. Enhanced Speeded Up Robust Features (ESURF)

Input: Pre-processed image (PI).
Output: Set of features.

Step 1: Load pre-processed image (PI).
Step 2: Call the procedure SURF.
Step 3: After Extraction, find the number of matching features using Euclidian distance.
Step 4: Discard the error matching features like outliers.
Step 5: Extract only the exact matching features using matching percentage.

This ESURF method detects one or more object in the given set of images and finds out the matching score using thresholds and accuracy measures under various conditions like rotation, orientation etc. This algorithm supports the accuracy for detection of objects in variant origin images from the dataset. By removing the outlying points, the distinction between the original image and the tampering image can be lowered. ESURF supports the real time images in the same way with data set images. The enhanced method increases the speed along with maintaining accuracy and the standard of its performance.

3.2. Particle Swarm Optimization

The PSO algorithm conserves and enhances the classification performance by repetitively determining the most relative and applicable features. The PSO methods determine only the optimum features. The number of features determined decides the performance of classifier. The Accuracy rate can be improved by not applying the too less or too unnecessary features. When compared with the other optimization algorithms, PSO is easy to implement and provides high computational efficiency. But PSO has a low converge rate in iterative process.

The number of particles is the most important parameter in the Particle Swarm Optimization. The collection of particles is also known as population size or swarm size. This algorithm works on the basis of '*n*' particles and position. The position of the particle is being restructured with the support of local and global positions of each and every particle around its neighbor. The optimal particles are searched by the particles by moving from corner to corner of the problem space. This process is then repetitively followed for a constant number of periods or until a minimum error is attained.
When there are a high number of input features, a particle swarm optimization technique can be utilized to explore the search area and locate an appropriate subset of features. This is improved by an optimization loop, which selects the best process parameter set for the feature extraction stage to improve classification accuracy.

Procedure 4. Particle Swarm Optimization (PSO)

Input: No of Particles N, Inertia Weight I, Acceleration Coefficient A_1,A_2 Random number R_1, R_2 Output: Global best
Step 1: Examine the objective function while assessing the position of each particle. $P = f(a,b) = \sin a^2 + \sin b^2 + \sin a \sin b$ Step 2: If the present position of a particle is finer than the prior one, it should be updated. If fitness of pi_i^t > fitness of p^b then $p_b = pi_i^t$ Step 3: Find the global best particle and update it If fitness of > g_b then $g_b = pi_i^t$ Step 4: Update particle Velocities $Vy_i = I\,Vy + A_1R_1(pb.\,i - pi) + A_2R_2(g_b.\,I - pi)$ Step 5: Move particles to their new position $pi_i^{t+1} = pi_i^{t+1} + Vy_i^{t+1}$ Step 6: Repeat the same process until the expected outcome is generated.

3.3. Classifier

Classifiers play a noteworthy role in image processing techniques. It is used to classify the features taken from the input image into several classes based on various criteria. Picture classification is the process of finding and classifying groups of pixels or vectors inside the image based on a set of rules. The image classification algorithm analyses the input photographs and generates an output classification that determines if the disease is present. To determine whether given input variables are related to the class, a classifier employs some training data. When the classifier has been properly trained, it can be used to identify unfamiliar emails. Classification is a type of supervised learning in which the input data is also delivered to the objectives.

3.3.1. Ensemble

An ensemble is a very good supervised learning algorithm which is used to make predictions. It is very flexible in representing the functions. The over fitting of the training data is reduced by some of the ensemble techniques. If there is a specific diversity in the given models, the ensemble classifier yields better results.

When stack up against other single classifiers, ensemble enhances the accuracy of prediction [13]. It is one of the best machine learning approaches that merges the predictions from various multiple models and provides improved predictive performance.

Procedure 5. Ensemble

Input: Training & Test Data sets Output: Combined Classifier C
Step 1: Train the prediction model $h_T(x)$ on the subset $T = \{1, \ldots .N\}$ Step 2: Final ensemble = combine the predictions of all the models $h_T(x)$. Step 3: To classify, majority vote or average class score can be used. Step 4: $MajorityVote = \arg\max\left\{\frac{1}{N}\sum_{T=1}^{N} h_t(x, C_i)\right\}$ where C is the class predicted by most models Step 5: Average value = $\left\{\frac{1}{N}\sum_{T=1}^{N} h_t(x)\right\}$

3.3.2. Back Propagation Neural Networks

It is an important technique to enhance the accuracy of predictions in Machine learning. BPNN algorithm gets the weights from output towards input. It is used to find out the derivatives as quick as possible. First the target output is initialized and the output of the hidden layer and output layer are calculated. Then the error is calculated by subtracting the desired output from the actual output. By adding all h errors, Total error is calculated. Until the threshold error is greater than or equal to total error, the execution will not be stopped. Otherwise, the same steps are followed iteratively. Image recovery and Image reconstruction performance is enhanced with the help of BPNN algorithm. It works best in high quality images. It also yields higher construction accuracy. The shapes and edges of the images are clearly observed by the BPNN to produce accurate results.

Procedure 6. Back Propagation Neural Networks (BPNN)

Input: Training & Test Images Output: Calculated Accuracy
Step 1: Input the features through the pre-connected path Step 2: Input is modeled using randomly selected real weights RW Step 3: Calculate the output and find out the errors in the output Error = Actual Output – Desired Output Step 4: Adjust the weight RW and execute the step 3 until the desired output is achieved. $RW_{ij}' = RW_{ij} + \Delta RW_{ij}$

3.3.3. Support Vector Machine

It is mainly used in regression and classification models. It is a comprehensive machine learning approach that may be used for classification, regression, and outlier detection in addition to classification and regression. But widely used in classification, with less computation and provides good accuracy [14]. This SVM creates a line which separates the data into classes. Initially the points closest to the output line are detected. These points are known as support vectors. After that, the line's and points' distances are determined. The calculated distance is called as margin. Maximizing the margin, improves the performance. Other data points are of no use to determine the decision surface.

With less data, SVM provides better results with reliability and accuracy [15]. Depending on the support vectors, SVM is highly stable and it is not influenced by outliers. It also works well with unstructured and semi structured data. It also works well with high dimensional data [16]. The problem occurs when the large data set is applied because the time taken for training the data set is very high.

Procedure 7. Support Vector Machine (SVM)

Input: Feature Vectors Output: Calculated Accuracy
Step 1: Input the feature vectors Step 2: Find a separating line between the features. Step 3: Identify the support vectors S_v closest to the line. Step 4: Compute the distance between the line and the support vectors. Step 5: Maximize the margin $M_g = \frac{2}{\|w\|}$ Step 6: The hyper plane which have maximum margin is the optimal hyper plane $y_i\left(w_i^T x_i + b\right) \geq 1,\ (x_i, y_i),\ I = \{1,\ldots,n\}$

4. Results and Discussions

This section presents the outcomes obtained from both existing and proposed algorithms. These methods are implemented with the real time images on Matlab 2019a and the performance indicators for classification are tabulated in Table 1.

Table 1. Performance indicators

Metrics	Formula
Accuracy	$\frac{\text{Number of Correct Predictions}}{\text{All of the Predictions}}$
Precision	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$
Recall	$\frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$
Time	Execution Completed – Execution Started
Percentage of Tampering	$\frac{1-\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)}}{2}$

The Figure depicts the different input images which have been tampered. The main plan of the proposed work is to find out the type of manipulation done that classifies an image as tampered or original. There are many ways to identify the tampered or manipulated images such as checking the edges, examining the shadows, missing reflections, looking for the signs of cloning, etc. The context-based image tampering methods are applied over the images in Figure 2.

Image 1	Image 2	Image 3	Image 4	Image 5

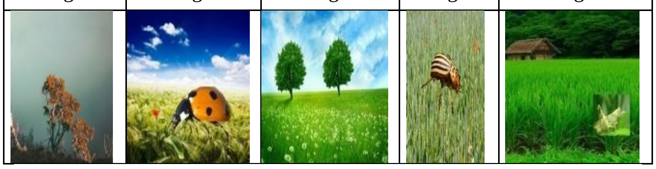

Figure 2. Random input images

The Table 2 shows the feature extraction points before optimization of different algorithms namely LBP, ELBP, SURF and ESURF applied to all the input images in Figure 2. SURF is considered to be a robust, low dimensionality feature detector and descriptor. It is outsourced that the proposed ESURF Algorithm produces the higher feature extraction points as 196 when compared to other existing algorithms HOG, LBP, SURF and Enhanced LBP.

Table 2. Feature extraction points before optimization

Algorithm	Feature Extraction Points
LBP	156
ELBP	173
SURF	167
ESURF	196

The Table 3 states that the ESURF when it gets optimized with PSO, it outsources the better results when compared to all other algorithms such as PSO_LBP, PSO_SURF and PSO_ELBP.

Table 3. Feature extraction points after optimization

Algorithm	Feature Extraction Points
PSO_LBP	140
PSO_ELBP	165
PSO_SURF	159
PSO_ESURF	183

The ESURF detector is applied to extract sufficient key points on smooth regions and texture regions as shown. The possible duplicated regions in test images can be found by matching the descriptors vectors. As shown in Figure 3, the identified forgery area of an image is the result of the forgery region extraction technique. It also claims that the suggested ESURF algorithm outperforms all other algorithms. The ESURF detector is applied to extract sufficient key points on smooth regions and texture regions as shown. The possible duplicated regions in test images can be found by matching the descriptors vectors. The main points in Figure 3 that are labeled are those that are suspected of not being the original content of a picture. In the figure the tampered region is shown in green color markings which make us to better understand that those regions are tampered. The picture substantiation and tampering localization technique outperforms state-of-the-art methods under diverse attacks, according to experimental results on various images with tampering of variable size and position.

The Ensemble classifier minimizes bias and variance which in turn increases the accuracy of models. From the Table 4, it is proved that the proposed PSO_ELBP yields better percentage of tampering such as 4.25, 4.89, 5.13, 5.48, 4.15 for the input images 1, 2, 3, 4 and 5, respectively. The precision, accuracy, Recall and Time are calculated and the outcomes are tabulated in the table 3. The PSO_ELBP produces better results in percentage of tampering when compared to the enhanced algorithm PSO_ESURF.

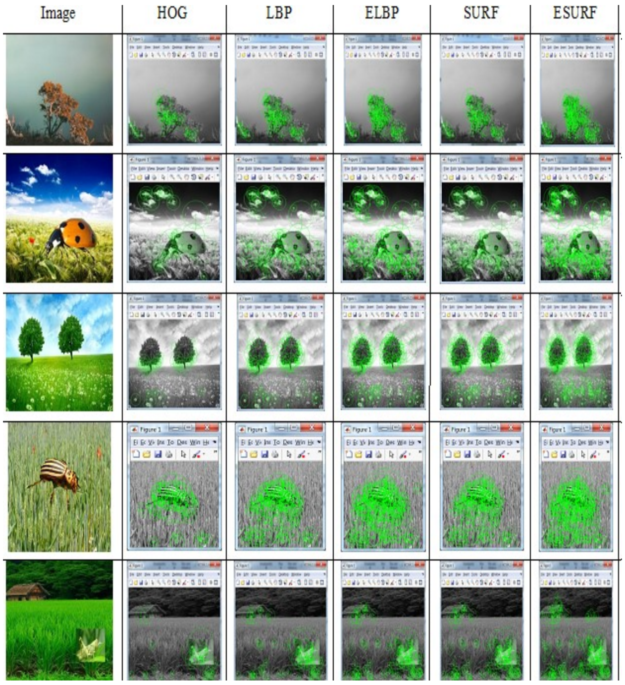

Figure 3. Tampered output images

Table 4. Classification using ensemble classifier

Algorithm	Image	Accuracy	Precision	Recall	Time	Percentage of Tampering
PSO_HOG	Image 1	94	93	94	4.1	4.7
	Image 2	94	93	94	4	4.6
	Image 3	95	94	95	4	4.6
	Image 4	94	93	94	4	4.6
	Image 5	94	93	94	4	4.6
PSO_LBP	Image 1	96	95	96	3.8	5.3
	Image 2	96	95	96	3.8	4.8
	Image 3	96	95	96	3.9	4.9
	Image 4	96	95	96	3.8	5.9
	Image 5	96	95	96	3.8	5.7
PSO_ELBP	Image 1	97	96	97	3.6	4.25
	Image 2	96	95	96	3.8	4.89
	Image 3	97	96	97	3.6	5.13
	Image 4	97	96	97	3.5	5.48
	Image 5	97	96	97	3.6	4.15
PSO_SURF	Image 1	98	97	98	3.5	3.1
	Image 2	97	98	97	3.1	2.5
	Image 3	97	98	97	3.4	3.6
	Image 4	98	97	98	3.2	3.8
	Image 5	99	98	99	3.1	2.98
PSO_ESURF	Image 1	98	97	98	3.2	3.7
	Image 2	99	98	99	3.1	4.3
	Image 3	99	98	99	3.2	5.7
	Image 4	98	97	98	3.2	4.8
	Image 5	99	98	99	3.1	4.2

The Table 5 illustrates the classification using BPNN classifier. The result shown in table.4 records that the percentage of tampering of PSO_ESURF is better when compared to other algorithms such as PSO_SURF, PSO_ELBP, PSO_LBP and PSO_HOG. The percentage of tampering for different images 1,2,3,4 and 5 are documented as 4.3, 5.6, 4.56, 5.14 and 4.1 respectively. So, it is concluded that the proposed PSO_ELBP is the preeminent method when compared to the proposed PSO_ESURF which is evaluated using BPNN classifier.

Table 5. Classification using BPNN Classifier

Algorithm	Image	Accuracy	Precision	Recall	Time	Percentage of Tampering
PSO_HOG	Image 1	90	89	90	4.9	5.1
	Image 2	91	90	91	4.8	5.2
	Image 3	90	89	90	4.9	5.3
	Image 4	90	89	90	4.9	5.1
	Image 5	91	90	91	4.8	5.1
PSO_LBP	Image 1	91	90	91	4.5	3
	Image 2	92	91	92	4.6	5
	Image 3	91	90	91	4.6	4.26
	Image 4	92	91	92	4.5	5.69
	Image 5	92	91	92	4.6	4.75
PSO_ELBP	Image 1	93	92	93	4.2	3
	Image 2	92	91	92	4.2	4.6
	Image 3	92	91	92	4.3	5.4
	Image 4	93	92	93	4.2	5.36
	Image 5	93	92	93	4.2	4.51
PSO_SURF	Image 1	96	95	96	3.5	3.4
	Image 2	97	96	97	3.2	4.3
	Image 3	97	96	97	3.1	5.4
	Image 4	96	95	96	3.2	4.8
	Image 5	97	96	97	3.5	4.2
PSO_ESURF	Image 1	93	92	93	4.1	4.3
	Image 2	93	92	93	4	5.6
	Image 3	94	93	94	4	4.56
	Image 4	94	93	94	4	5.14
	Image 5	94	93	94	4	4.1

The Table 6 demonstrates classification using SVM classifier. The performance of PSO_ELBP is found to be better to find the tampered part of the input images since the percentage of tampering is found to the highest such as 7.56, 7.52, 8.3, 7.65, 7.21 for the input images 1, 2, 3, 4 and 5, respectively. So, it is concluded that the proposed PSO_ELBP is the preeminent method when compared to the proposed PSO_ESURF which is evaluated using SVM classifier.

Table 6. Classification using SVM classifier

Algorithm	Image	Accuracy	Precision	Recall	Time	Percentage of Tampering
PSO_HOG	Image 1	85	84	85	6.13	4.9
	Image 2	86	84	86	6.2	4.7
	Image 3	85	84	85	6.14	4.9
	Image 4	85	84	85	6.15	4.8
	Image 5	86	85	86	6.13	4.6
PSO_LBP	Image 1	86	85	86	5.9	7.69
	Image 2	87	86	87	5.9	8
	Image 3	86	85	86	5.8	8.3
	Image 4	87	86	87	5.8	7.98
	Image 5	87	86	87	5.8	6.24
PSO_ELBP	Image 1	87	86	87	5.6	7.56
	Image 2	88	87	88	5.6	7.52
	Image 3	88	87	88	5.5	8.3
	Image 4	88	87	88	5.6	7.65
	Image 5	88	87	88	5.7	7.21
PSO_SURF	Image 1	87	86	87	5.6	3.8
	Image 2	88	87	88	5.6	4.8
	Image 3	88	87	88	5.5	4.7
	Image 4	88	87	88	5.6	5.6
	Image 5	88	87	88	5.7	5.1
PSO_ESURF	Image 1	89	88	89	5.3	7.51
	Image 2	88	87	88	5.2	8.2
	Image 3	89	88	89	5.3	7.43
	Image 4	89	88	89	5.1	6.98
	Image 5	88	87	88	5.3	7.12

5. CONCLUSION

As different methods of image forgery have been developed and used, earlier algorithms such as SURF and LBP for copy-paste, retouching, splicing, and copy-move or cloning type of forgery detection were considered. The proposed method ESURF and ELBP uses combination of Particle Swam Optimization feature extraction. The accuracy, precision, recall, time and percentage of tampering are calculated for each proposed algorithm. The proposed algorithms' evaluation is conducted using several classifiers such as Ensemble, BPNN, and SVM. From the values recorded in the Tables 3, 4 and 5 it was concluded that using all the three classifiers, the percentage of tampering is found to be better in PSO_ELBP. PSO_ELBP records the highest percentage of tampering than PSO_ESURF. In future many other classifiers and feature extraction algorithms can also be used and compared to detect the tampered part of the input images.

REFERENCES

[1] S.S. Ali, I.I. Ganapathi, N.S. Vu, S.D. Ali, N. Saxena, N. Werghi, "Image Forgery Detection Using Deep Learning by Recompressing Images", Electronics, Vol. 11, No. 3, p. 403, January 2022.
[2] H. Ding, L. Chen, Q. Tao, et al., "DCU-Net: A Dual-Channel U-shaped Network for Image Splicing Forgery Detection", Neural Computing and Applications, Special Issue on Machine Learning for Security and Privacy: Advancing the state-of-the-art applications, pp. 1-17, August 2021.
[3] D. Srivastava, R. Bakthula, S. Agarwal, "Image Classification Using SURF and Bag of LBP Features Constructed by Clustering with Fixed Centers", Multimedia Tools and Applications, Vol. 78, No. 11, pp. 14129-14153, October 2018.
[4] S. Kukreja, G. Kasana, S.S. Kasana, "Extended Visual Cryptography-Based Copyright Protection Scheme for Multiple Images and Owners Using LBP-SURF Descriptors", The Visual Computer, Vol. 37, No. 6, pp. 1481-1498, July 2020
[5] A. Słowik, "Swarm Intelligence Algorithms", CRC Press Taylor and Francis Group, pp. 1-362, Boca Raton, Florida, USA, August 2020.
[6] R. Singh, N. Rajpal, R. Mehta, "An Empiric Analysis of Wavelet-Based Feature Extraction on Deep Learning and Machine Learning Algorithms for Arrhythmia Classification", International Journal of Interactive Multimedia and Artificial Intelligence, Vol. 6, No. 6, pp. 25-34, June 2021.
[7] K. Merriliance, R. Veeralakshmi, "Feature Extraction of Melanoma Data using Machine Learning Techniques", Design Engineering, Vol. 6, No. 9, pp. 5352-5360, July 2021.
[8] M. Elaziz, K. Hosny, A. Salah, M. Darwish, S. Lu, A. Sahlol, "New Machine Learning Method for Image-Based Diagnosis of COVID-19", PLOS One, Vol. 15, No. 6, p. e0235187, June 2020.
[9] S. Baghdadi, N. Aboutabit, "Illumination Correction in a Comparative Analysis of Feature Selection for Rear-View Vehicle Detection", International Journal of Machine Learning and Computing, Vol. 9, No. 6, December 2019.
[10] P. Dhar, "A New Flower Classification System Using LBP and SURF Features", International Journal of Image, Graphics and Signal Processing, Vol. 11, No. 5, pp.13-20, May 2019.
[11] N.S.A. Alsandi, "Image Splicing Detection Scheme Using Surf and Mean-LBP Based Morphological Operations", Science Journal of University of Zakho, Vol. 9, No. 3, pp. 178-183, July 2021.
[12] B. Nithya, P. Sripriya, "Feature-Level Fusion of Multimodal Biometric for Individual Identification by Training a Deep Neural Network", Springer, Vol. 311, pp. 145-159, Singapore, January 2022.
[13] R.S. Akinbo, O.A. Daramola, "Ensemble Machine Learning Algorithms for Prediction and Classification of Medical Images", Intechopen, Vol. 1, No. 1, pp. 55-65, London, England, December 2021.
[14] M. Murugappan, A. Mutawa, "Facial Geometric Feature Extraction Based Emotional Expression Classification using Machine Learning Algorithms", PloS One, Vol. 16, No. 2, P.e0247131, February 2021.
[15] C.K. Sarumathiy, K. Geetha, C. Rajan, "Improvement in Hadoop performance using integrated feature extraction and machine learning algorithms", Soft Computing, Vol. 24, No. 1, pp. 627-636, October 2021.
[16] P.N. Leukemia, "Drug Prediction Using Machine Learning Techniques with Feature Engineering", Journal of Advanced Research in Dynamical and Control Systems, Vol. 12, No.4, pp. 141-146, July 2020.
[17] J.N Victor, "A Profit Driven Stacking Model for Effective Churn Prediction", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 50, Vol. 14, No. 1, pp. 89-94, March 2022.
[18] A. Dhandayuthapani, J. Lawrence, "Plant Disease Recognition Using Optimized Image Segmentation Technique", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 50, Vol. 14, No. 1, pp. 211-218, March 2022.

BIOGRAPHIES

Dharmalingam Umamaheswari was born in Coimbatore District, Tamilnadu, India in 1983. She completed her M.Phil. in 2011 and pursuing her Ph.D. from Department of Computer Science, Government Arts College, Udumalpet, TamilNadu, India. Now she is working as Assistant Professor in Nallamuthu Gounder Mahalingam College, Pollachi, India. She has 14 years of teaching experience. Her areas of research interest include data mining, image processing and machine learning. She has published nearly 10 papers in national and international journals.

Eswaramorthy Karthikeyan was born in Palani, Dindigul District, Tamilnadu, India in1974. He completed the Ph.D. degree from Gandhigram Institute of Technology, Dindigul, India in 2008. Currently, he is working as Head of Department of Computer Science, Government Arts College, Udumalpet, Tamil Nadu, India. He has 25 years of teaching and research experience. He completed research projects funded by UGC (Major Research Project), TANSCHE, TANSCST. He organized so many seminars/workshops/conferences and received funds from agencies like UGC, CSIR, TANSCHE, and TANSCST. He also guided 10 Ph.D. students and guiding 4 students. He is an Editor-in-Chief of International Journal of Advanced Networking and Applications (IJANA). He delivered lectures in many colleges and chaired in many conferences. He published a book entitled "A Text Book on C: Fundamentals, Data Structures and Problem Solving" by PHI. His areas of research interest include advanced networking, and cyber security. He has published more than 60 papers in various national and international journals.