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A Hierarchical Support Vector Machines for Weapons Identification Using Multiple Stabbed Wound Images

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Abstract: This paper proposes hierarchical support vector machines for weapon Identification using images of repeated stab wound patterns caused by sharp metal weapons used in homicidal cases and also presents a comparative study with standard flat support vector machine. The methodology includes the segmentation technique for the extraction of region-of-interest in the image using transition region-based segmentation algorithm and then texture, shape and size features were extracted from the segmented image. For multiple classes, a hierarchical support vector machine is adapted as a classifier. This approach gives a computationally interesting and efficient alternative solution to identify the weapons used in the crime; this method uses the digital images of repeated stab wound patterns which appear on the human body. The experimental study has three main stages, at the first stage includes generating of non-overlapping segments from the pattern, at the second stage the features of wound patterns are extracted and finally identification of patterns and its weapon of cause. The proposed method accuracy assessment is performed and also comparison study is performed with standard flat support vector machine and with the traditional method of forensic pathology. The experimental results achieved for Identification is 96.71% accuracy, with an available database of 500 images of a pattern consisting of repeated stabbed wounds. From the comparative study, the proposed methodology has given better results than standard SVM and traditional method. The proposed method delivers a better solution for identification from the image of the repeated stab wound pattern as there is no human intervention that reduces the error and data manipulation unlike traditional manual method.

Index Terms: Forensic, Identification, Patterns, Segmentation, Stab, Support Vector, Wounds.

1. Introduction

In the last decade, machine learning played a vital role in the identification of the objects. The same is influenced even in the forensic science disciplines and as well as in crime investigation. The influence has made a combination of forensic science and computer science to come together, and this encourages us to apply machine learning for the forensic science problems to create solutions, these solutions are known as computational forensics. Many problems of forensic science are implemented using machine learning such as fingerprint analysis, face recognition, bite mark analysis, blood spatter analysis, footprint analysis, firearm tool analysis, and document analysis. In addition to these, we propose a solution to one of the forensic science problems i.e., the weapon identification based on the wound pattern images. In order to develop such a methodology, we have considered the digital images of various repeated wound patterns which are caused by the sharp metals used in most homicidal cases. The wound patterns have certain characteristics based on the weapon used; each wound pattern has a certain shape, size and the variations in the pattern components [1]. The variations in pattern are possible to derive from the textural, shape and size features of the images. In this work, it is observed that information concerned with weapons variations, weapons' wound patterns after stabbing repeatedly and forensic techniques are fused with classifier algorithms for better result. Nevertheless, in traditional methods in which manual identification are carried out for the weapon in homicidal cases, which gives scope for data manipulation, human error and it depends on experts' knowledge for identification. Data manipulation in traditional methods refers to the modification to the report or making more damage to the human body (victim) especially wound region because of bribing/corruption. These disadvantages in the traditional method can be overcome by proposing a computational method for the identification of weapons based on wound patterns in which there will be no involvement of human beings. In this regard, the paper presents such methodology, in which the images of wound patterns are taken at the time of crime scene investigation. The work comprises of a specific number of sharp metals were considered for the analysis. It becomes more important to recognize the border of the wound and to figure its patterns. In this work, the initial step is to perform image segmentation to produce a set consists of non-overlapping segments by transition region-based object segmentation [3]; secondly, features will be extracted for the analysis of wound pattern, and finally the identification. To implement this methodology, we have considered the most widely used supervised learning; this learning usually derives a function that identifies the class for new samples based on a prelabeled training database. Two commonly used methods in supervised learning are a binary classification for two classes and multi-class classification for more than two classes. The classifiers can be used in two different approaches, firstly, flat classification approach in which a single classifier is used to assign objects to the classes based on the features set and secondly, hierarchical classification approach in which more than one classifier is used to build hierarchical structure i.e., classifiers at every level of the classification process, this type of process are important in real-world classification. There are two main advantages of using the second approach: the combined classifiers discover data about parent-child class associations in the hierarchy and, if the classes are more in numbers, classifiers will get least affected if there is an increase in problem complexity. Among these models, one of the nonparametric classifiers is support vector machines (SVM), which are effectively used for the classification of images as it describes the complex nonlinear relationships. In this work, we evaluated the two cited methods for the weapon identification and mapping of four major weapons used commonly in homicidal cases from the images captured during a crime investigation. SVM method is adapted as main classifiers based on its popularity, verified and effective performance in many applications. Identification from a traditional method reported significant confusion occurred in certain weapon characteristics, wound patterns and forensic experts. Although few miss-classifications might be acceptable for a database considerable accuracy is required for accurate classification. Therefore, we computed the efficiency of machine learning methods, either as flat or hierarchical methods, for improving identification results. The classifiers were trained and tested using shape, size and textural features extracted for identification, which quantify the effect of features selected in the results.

2. Literature Survey

Many researchers have used traditional and medical techniques for classification whereas others used experimental techniques for segmenting the images followed by classifier Artificial Neural Network [1, 2] and fuzzy logic methods for classifying the wound [3,4]. Another system proposed has automated image segmentation, identification, and classification of the wound region [5]. Various approaches of Artificial Neural Networks, Multi-Layer Perceptron and Radial Basis Function along with parameters derived using cross-validation approach, then supervised learning is applied for the prediction procedure of the wound classification and later results are compared with conventional methods [6,7]. Some of the techniques proposed by researchers, determine precise patterns of wounds and distribution of injuries and then thereafter manual pattern matching method is conducted [8,9]. The Image comparison techniques (that has side-by-side image observation), is also used in identifying and classifying the wound patterns [10,11]. The most common methodologies used in identification and classification is by autopsy procedure in which unusual damage was found around the wound which is unacceptable in the investigation, that shows wound was got affected with great force, using some odd-shaped sharp object [12,13]. And also, a comparative analysis is done with two weapons in order to identify and classify the compatibility with the patterns of wound found on the human body [14]. Some researchers proposed a model and system which effectively assesses and identifies the weapons from a huge collection of weapons, the technique was multiple-criteria based fuzzy decision-making concept [15]. Many researchers and academicians used morphometric factors that unify presentation of local structure i.e., thickness, orientation, and anisotropy parameters that are helpful in identifying the shape of the object [16]. And researchers also proved that "selecting the proper set of features that can make a major difference in classification" [17]. Consequently, "these analyses led us to the classification of the murder weapon and the author of the crime" [18, 19]. A simple but effective method to be adopted for the identification and classification that makes selection objective and consistent [20].

3. Methodology

Since the proposed method is going to classify the weapons with respect to wound patterns, wound pattern part is the only image object of interest in our work. The aim of segmentation is to detect and highlight the region of interest (ROI), then the required features are extracted from the segmented image for the classification process. The execution of the model in weapon and wound patterns dealing with obliges openness of calculations that could isolate differing case of wounds in images is processed. Fig. 1 shows the proposed system for the identification and classification of weapons in case of the repeated stabbed wound patterns.

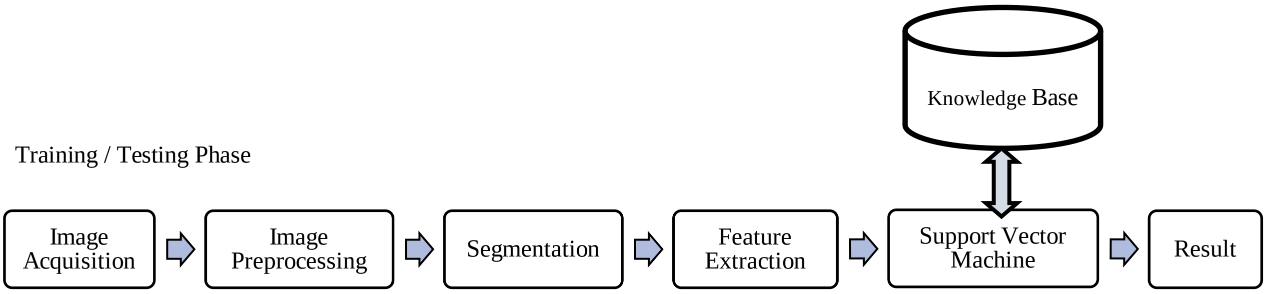


Fig. 1. Block diagram of Proposed Methodology

The proposed methodology intended to identify the different weapons considering the samples of the wounds created by the weapons which were collected as evidence in the homicidal case investigations; additionally, the proposed methodology is compared with the standard flat SVM method to figure out which of the approach gives higher accuracy and precision in the identification process. The proposed methodology involves segmentation technique for separating the ROI from the overall input image, and later segmented image is used to extract the features for the identification process through SVM.

3.1. Image Acquisition

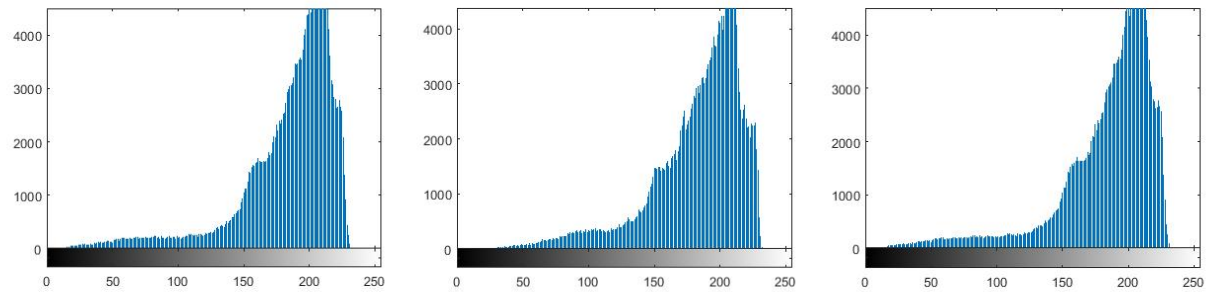
The digital camera is used in capturing the required images with a standard resolution under controlled conditions (Fig. 2 for image sample). The controlled condition specifies that there are no further damages made to wound region and victim body. The images acquired consist of the wounds and other areas of the body and are processed to focus on the actual wound region i.e., shape. In this acquisition, all the images are assumed to have the same resolution, and if images acquired are of different resolutions, then these are resampled to a common resolution. The first and foremost stage of the approach is to separate wound region from the image using segmentation, and then features are extracted from the focused area. To get better measurable features, the image quality is improved by applying the sharpening using spatial filtering.

(a) (b) (c)

Fig. 2. Sample Images of repeated stab wound patterns (a) & (b) Double edged knife (c) Star screwdriver

3.2. Image Preprocessing

Preprocessing of images suggestively increase the optical inspections' reliability. There are many filter operations are available, which increase or decrease certain image details that enable easier or faster evaluation.



(a) (b) (c)

Fig. 3. Spatial filtering Histograms (a) Original Image (b) Gaussian filtering mask (c) Final image after the filtering process

In this, the images are improved using spatial filtering which is an essential process in image processing. The filtering is used for enhancement of images, reduction of noise, sharpening. Spatial filtering is given by equation (1)

$$s(x, y) = \sum_{m=-M/2}^{M/2} \sum_{n=-N/2}^{N/2} h(m, n) f(x - m, y - n) \quad (1)$$

where h(m, n) is Gaussian filtering mask of size M x N.

3.3. Transition Region-Based Segmentation

Precisely, pixels in image objects are based on a measure of feature vectors (size, shape, and texture features) and also on the basis of neighborhood context that surrounded the pixels. To get useful information from the digital image, firstly the image need to be segmented to get the region-of-interest or object. This segmented object from the image is an unclassified object that is further used for analysis and to assign it to the class. Transition region-based segmentation technique is adapted and implemented for extracting the unclassified object from the digital images. General rules of imagery say that larger image objects are good for analyzing and if they are small then it must have clear outlines of an object. This will serve as basic building blocks for objects of interest for further analysis. Image segmentation is an important phase in the image classification process, as the segmented image is used for further processing i.e., feature extraction, analysis, and retrieval. Based on the literature review of various researchers, from the available segmentation techniques, transition region-based segmentation is adapted as it is one of the simple and effective segmentation techniques [1] and it overcomes the disadvantages of many segmentation techniques i.e., other segmentation techniques fail if the images are of varying intensities [1]. The transition region-based segmentation algorithm along with the explanation of each step is as given in algorithm 1.

Algorithm 1: Transition Region-Based Segmentation
Input: Original Image
Output: Segmented Image highlighting region of interest
Start
Step 1: Read Original Image and convert into a gray-scale image
Step 2: Extraction of the transition regions from an image

Geometrically positioned and composed of pixels with intermediate gray levels between object and background is known as transition region [1]. The local variance is important for finding transition region; hence, it is used as a factor for transition region extraction. For an m × m local neighborhood centered at pixel p(i, j), the local variance computed using equation (2):

$$LV(i, j) = \sigma^2 = \frac{1}{m^2-1} \sum_{x=1}^{m} \sum_{y=1}^{m} (f(x, y) - \bar{f})^2 \quad (2)$$

where (*x*, *y*) is local coordinate for a given neighborhood of the sub-image *f* and $\bar{f}$ is neighborhood's gray level mean [1].

Step 3: Apply morphological operations on results of step 2 to get edge image

The output obtained in step 2 has boundaries of object regions with more than 1-pixel width. To find edges with single-pixel width, morphological thinning is done by using equation (3).

$$\text{Thinning}(I, J) = I - \text{hitandmass}(I, J) \quad (3)$$

where 'I' is an image and thinning structuring element *J*. The thinning process generates single isolated pixels around edge image and to eliminate these types of pixels, the clearing morphological operator is applied on the outcome of the thinning process using equation (4)

$$F(x, y) = \begin{cases} I(x, y) & \text{if } (x, y) \text{is on the border of I} \\ 0 \text{ otherwise} \end{cases} \quad (4)$$

Step 4: To generate object counters – Apply edge linking

The output image of step 3 does not have complete connected edge pixels. To obtain complete connected pixels, the edge linking is applied in discontinuity area. The process of edge linking is: From every discontinuous edge pixel, 8-connectivity is checked till it encounters the endpoint and all endpoints are labeled with a number. Then distance is computed between adjacent endpoints having a different number. These adjacent endpoints are linked if the distance is less than or equal and unlabeled pixels are considered as isolated pixel and finally, object contours are extracted.

Step 5: To extract object regions – Apply morphological region filling

Firstly, morphological erosion is applied on object contours for the elimination of edge spikes which are useless, this generates exact perimeter of object contour and later region filling is applied to extract the object regions from the background [1].

Step 6: To extract the objects, replace the pixels of the object region with pixels of the original image.

The final object region extracted is in the form of binary i.e., '0' and '1' pixel values.\

Stop

(a) (b) (c)

Fig. 4. Images of Segmentation algorithm (a) Original Image (b)Gray-Scale Image (c)Final segmented Image

Table 1. List of Features for the identification of weapons

Sr. No.	Name of the Feature	Sr. No.	Name of the Feature
1	Area	7	Size-Invariant
2	Perimeter length	8	Eccentricity
3	Bounding box	9	Gray-Level Co-occurrence Matrix (GLCM)
4	Convex Hull	10	Correlation
5	Compactness	11	Shape Signature
6	Central Moments	12	Shape Matrix

3.4. Feature Selection and Extraction

If the texture, size or shape parameters are high in value, then the resulting objects can be optimized for spectral/spatial homogeneity. In machine vision, feature extraction begins with an initial set of measured data and then deriving values into features projected as informative and non-redundant for learning and simplification steps leading to better performance. Feature extraction is the process of dimensionality reduction, if input data to be processed is large for an algorithm and assumed to be redundant, and then it is transformed into a reduced set of features (known as feature vector). Selecting a subset of the derived features is called feature selection. The features selected are likely to contain relevant information of the input data (refer table 1 for selected features), this will help in performing the desired task using the reduced and selected features from initial data. The features are extracted by reading the segmented image and then computing the features is as given below:

3.4.1 Computation of Geometric Features from the image

Perimeter: Contour features like perimeter makes the objects distinguishable in terms of the same area but different perimeter. The perimeter equation is given in equation (5) and 0.95 constant value is multiplied with a perimeter to avoid overestimation.

$$P(R) = (0.95) \text{ x } \sum_{i=0}^{M-1} \text{length}(c_i') \tag{5}$$

with $\text{length}(c) = \begin{cases} 1 & for\ c = 0, 2, 4, 6 \\ \sqrt{2} & for\ c = 1, 3, 5, 7 \end{cases}$

Area: In pattern recognition and image processing, the object area is common and measured in terms of a number of pixels within the object boundary, i.e., after segmentation, the number of the pixels within each closed region (object) is the area of the object. Just counting image pixels that make closed region is given by equation (6):

$$A(R) = | R | = N \tag{6}$$

Bounding Box: Generally, any feature recognition/detection algorithm gives the region of interest in terms of pixel coordinates, width, and height; the starting coordinates are used along with width and height, the minimum axis-parallel box that enfolds all points in a region R is given by equation (7):

$$\text{BoundingBox}(R) = \langle u_{min}, u_{max}, v_{min}, v_{max} \rangle \tag{7}$$

Convex Hull: Boundary tracing and morphological methods are used in extracting convex hull feature for a finite point set S. α_i and x_i are points within region-of-interest [6]. With the given equation (8):

$$C = \left\{ \sum_{i=1}^{|S|} \alpha_i x_i \mid (\forall i : \alpha_i \geq 0) \wedge \sum_{i=1}^{|S|} \alpha_i = 1 \right\} \tag{8}$$

Compactness: Both area and perimeter are vital features in image processing, the compactness is derived using a combination of these two features to create a relatively unified value of size. This compactness is given by Eq.9 as follows:

$$\mathrm{Compactness} = \frac{P^2(R)}{A(R)} \tag{9}$$

where P(R) is perimeter and A(R) is the area of region-of-interest R.

3.4.2 Computation of Statistical Shape Features

Central Moments: Central moments computes characteristic properties w.r.t its centroid. The centroid of a binary region is arithmetic mean of all (x, y) coordinates in the region is given by equation (10):

$$\bar{x} = \frac{1}{|R|}\sum_{(u,v)\epsilon R} u \text{ and } \bar{y} = \frac{1}{|R|}\sum_{(u,v)\epsilon R} v \tag{10}$$

The centroid is an only specific case of the more general concept of the moment, the ordinary moment of order *(p, q)* for discrete (image) function *I(u, v)* is given equation (11):

$$m_{pq} = \sum_{(u,v)\epsilon R} I(u,v).\, u^p v^q \tag{11}$$

Size-invariant: Moments are familiar in many applications of image analysis; however, *moment invariants* are invariants that are derived from moments. **Size-invariant** features can be obtained by scaling central moments uniformly by some factor s

$$\text{Size\_Invariant} = s^{(p+q+2)} \tag{12}$$

Eccentricity: This feature is computed by considering the semi-major axis ***a*** and semi-minor axis ***b*** of ROI and is given by equation (13), we get the eccentricity E:

$$E = \sqrt{1} - b^2/a^2 \tag{13}$$

Shape signature is a shape derived 1D function from shape boundary points. In this, derived function selected is "to compute the centroid distance function". Centroid distance function r(t) gives the distance from boundary points to centroid (g_x, g_y) of region-of-interest:

$$r(t) = \sqrt{[(x(t) - g_x)^2 + (y(t) - g_y)^2]} \tag{14}$$

where (x(t), y(t)) with t=0, 1, ..., L-1 are coordinates of each pixel and L is the number of pixels in binary shape boundary of the image.

Shape matrix is a sparse sampling of shape; a shape based on areas of shape in concentric rings (Ci) that are relative and located in shape center of mass [6] and is given by equation (15):

$$X_i = A(S \cap C_i)/A(C_i) \tag{15}$$

where A is area function and S is the shape of region-of-interest.

3.4.3 Computation of Texture features

Gray-Level Co-occurrence Matrix (GLCM): GLCM is defined as co-occurring pixel values distribution for the given offset. The image having K different pixel values, the K x K co-occurrence matrix *C* is defined for an n x m image *I* with an offset (Δ_x , Δ_y), as given in equation (16):

$$C_{\Delta_x,\Delta_y}(i,j) = \sum_{x=1}^{n}\sum_{y=1}^{m}\begin{cases}1, & I(x,y) = i \text{ and } I(x+\Delta_x, y+\Delta_y) = j\\ 0, & \text{otherwise}\end{cases} \tag{16}$$

where i and j are the pixel values; x and y are the spatial locations in the image I; and I(x, y) indicates pixel value at pixel (x, y).

Correlation determines the degree of similarity between data sets, correlates the spatial domain with frequency-domain processing and is given by equation (17):

$$\text{Correlation} = \frac{\sum_{x,y}[(xy)P(x,y)] - \mu_x\mu_y}{\sigma_x\sigma_y} \tag{17}$$

where, μx, μy are means and σx, σy are standard deviations.

3.5 Hierarchical Support Vector Machine Classifier

The goal of this work is to evaluate the accuracy of the SVM classifier for identification. The framework for measuring the accuracy of SVM for the given dataset is composed of the stages given below:

1) Preprocessing of the images in the dataset – explained in section 3.2

2) Dataset Separation into training and test datasets – In this work, an available dataset of 500 images is divided into two separate datasets (training dataset and testing dataset) of 250 images each.

3) Choice of training – the way of training includes a method of training multiclass, the value of the penalty term and choice of kernel.

4) Training, Testing, and evaluation of the performance

3.5.1 Method of multi-class training

SVMs are considered for binary classification, and when dealing with multiple classes as in image classification, one needs an appropriate method. A methodology with multiple SVM is considered that incorporates multiclass learning. A hierarchical SVM method is considered in this work, this classifier method consists of multiple levels and at every level a separate SVM classifier is considered (like a tree structure, for every binary branching - one SVM classifier is considered) i.e., combining binary classifier in “One Against One” [Pontil and Verri, 1996] at every level and branch of tree structure.

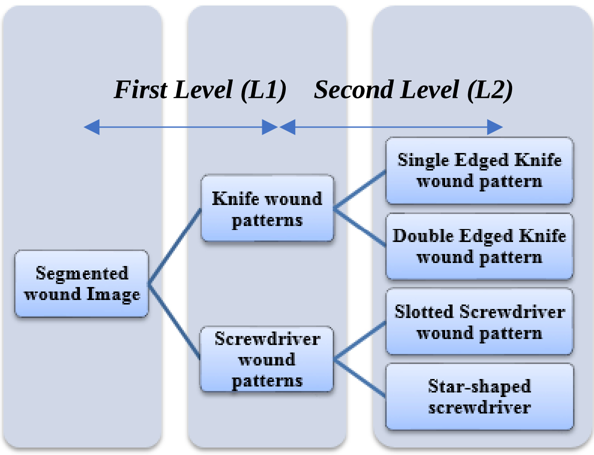


Fig. 5. Support Vector Machine for Proposed Methodology (Hierarchical SVM)

This hierarchy structure is as shown in Fig. 5, differentiating the classes for which each classifier is trained. The number of levels in this methodology (as we considered four classes) are two L1 and L2 as described below:

(1) The first level (L1) is given by first SVM classifier, which is trained using a complete set of objects named as “Knife wound patterns” or “Screwdriver-wound patterns”.

(2) The second level (L2) is formed by two different SVM, one for each group of wound patterns. Each classifier is trained using objects belonging to each group (single-edged knife and double-edged knife for knife wound group, slotted screwdriver, and star-shaped screwdriver for screwdriver wound group).

Once the three classifiers (one classifier at first level and two at the second level) are obtained, the classification is carried out by first applying L1-SVM to decide if the wound is a knife-wound pattern or screwdriver-wound pattern and then using the corresponding L2-SVM classifiers to decide final class.

3.5.2 Choice of the kernel

The kernel is the only the parameter of SVM that is adjustable, it has to be selected carefully because an inappropriate kernel can give poor performance. Different kernels are available for SVM; they are linear, polynomial, Radial Basis Function (RBF) and Neural Network (NN). Based on the literature survey of SVM, the kernel selected for this work is RBF kernel. When the input data are images, the RBF kernel is represented as in equation (18):

$$K(x, y) = e^{-\frac{||x-y||_2^2}{2\sigma^2}} \tag{18}$$

The kernel K will provide good performances, in case of images as input data, the norm seems to be quite meaningful and because of this reason, RBF kernels gives good results.

3.5.3 Training, Testing SVM and Evaluation of Performance

The number of training samples in the dataset used in this work are 250 images comprises of all wound types belongs to the four classes. Since hierarchical SVM emphasizes the multiple class relationships rather than single huge classifier, the identification is carried out with the classifier's cooperation built at each level of the tree structure. The training dataset is organized into two levels of the tree; each level represents classes or subclasses in a classification tree. There are two classes at level L1 and four classes at level L2; the classifiers at each level are trained using the associated datasets of all the class and subclasses. That is level L1 classifier is trained with all classes and level L2 classifier is trained with related subclasses. After the training of all classifiers at all levels, the trained model is used for testing the unknown sample. In this work, the accuracy of the classifier is tested using the testing dataset. Since the class from which the test images were selected is known, the accuracy of the classifier is evaluated how often the classifier assigns the test images to the classes from which they originally came. However, the accuracy, precision, recall, and F-measure of classification are used as evaluation measures. For further comparative evaluation, whether the proposed method is performing better than the other SVM possibilities; a standard flat SVM classifier is also considered in this work in which a single SVM classifier is used for multiple classes and there is no levels/hierarchy. This flat SVM is trained and testing with the same dataset as mentioned in hierarchical SVM and the kernel for the flat SVM is also the same RBF kernel. The comparison of the two methods, flat and hierarchical SVM is explained in results.

4. Results and Discussion

Quantitative results of proposed methodology show a good summary of the performance in comparison with flat SVM approach for the same set of data and the variations in the performance of the methods is observed. Hence, the hierarchical SVM based identification is more suitable for mapping needs when it deals with multiple class and moderate resolution images as it is captured during a crime investigation. The entire images dataset consists of 500 images; this dataset is divided into two separate datasets for training and testing (250 images in each dataset). The proposed method is trained with training dataset consist of 250 images and tested thoroughly on a testing dataset of 250 images. This dataset is equally distributed for all the types of wounds with respect to weapons.

4.1 Results of Flat and Hierarchical Support Vector Machine

The transition region-based segmentation is used to generate image objects that have given characteristics of relations between different sized adjacent objects. Transition region-based segmentation strategy assembles the objects to generate larger objects and is based on selected scale, texture, size and shape features. For each individual image object, 12 features were extracted for classifier; each object class has distinguishable features making it different from other objects. The feature extraction is carried out for selected features to identify the distinguishable features of the objects that determine wound patterns and its weapon of cause and to get appropriate threshold values for separating the classes. To achieve this target and to identify the distinguishable features for object classes for classification, two-level SVM is proposed and implemented. On the basis of these characteristic training data for all wound patterns and its weapons class, the probability distribution for the classes is estimated and used to compute the separability between classes. The outcomes of all combinations for separation of the classes are presented in Table 2. Finally, the classes are determined by classification with the defined functions for all classes which were classified separately. A Confusion Matrix is a prominent portrayal of the execution of characterization models. Table 2 gives us the number of accurately and erroneously classified examples, contrasted with the actual outcome in the test dataset.

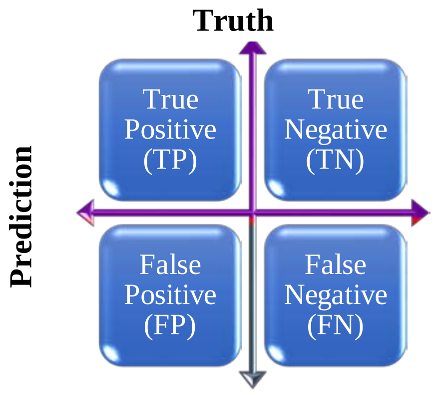


Fig. 6. Confusion Matrix

The advantage of utilizing confusion matrix as an assessment tool is that it permits analysis in detail, (for example, if the model is confounding two classes) than the basic extent of effectively classifying the samples (accuracy) which can mislead results if the dataset is not balanced. The least complex classifiers, called as binary classifiers, have just two classes: positive or negative. Binary classifiers' performance is condensed in a confusion matrix that cross-arranges anticipated and observed samples into four choices: (a) True Positive (TP) - Correctly label prediction, (b) True Negative (TN) - Correctly other label prediction, (c) False Positive (FP) - Falsely label Prediction, and (d) False Negative (FN) - Missing and approaching label.

Table 2. Performance Measures of Confusion Matrix with comparison

Measure	**Derivations**	**Standard Flat SVM**	**Hierarchical SVM**
Sensitivity	TPR = TP /(TP + TN)	0.9091	0.9804
Specificity	SPC = TN / (FP + TN)	0.3750	0.6667
Precision	PPV = TP / (TP + FP)	0.8889	0.9852
Negative Prediction Value	NPV = TN / (TN + FN)	0.4286	0.6000
False Prediction Rate	FPR = FP / (FP + TN)	0.6250	0.3333
False Discovery Rate	FDR = FP / (FP + TP)	0.1111	0.0148
False Negative Rate	FNR = FN / (FN + TP)	0.0909	0.0196
Accuracy	ACC = (TP + TN) / (P + N)	0.8269	0.9671

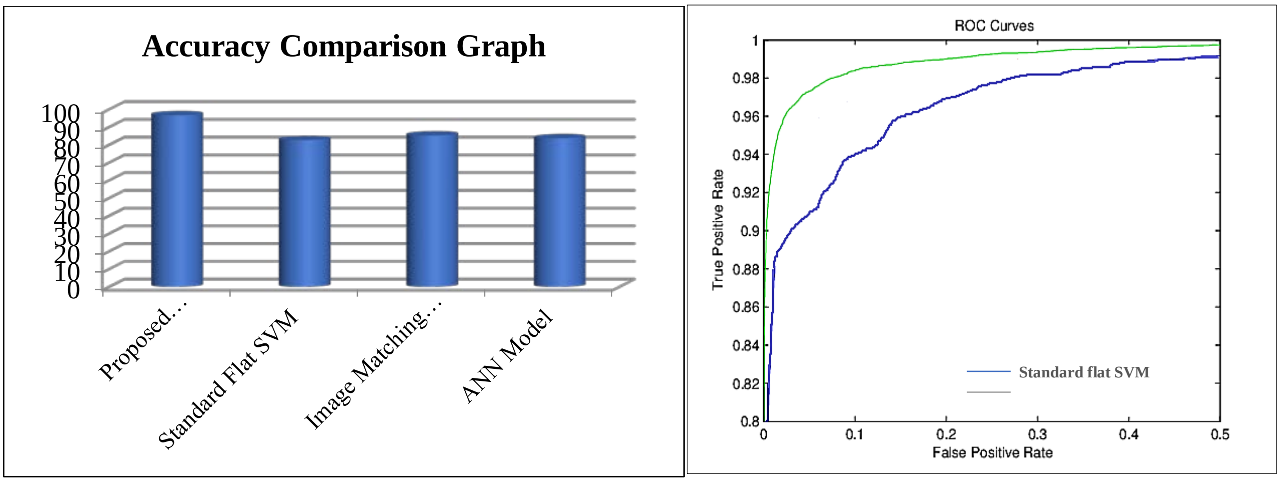
4.2 Comparison of Results

The hierarchical SVM is tested and performance is compared with the flat SVM classifiers. Based on the literature survey and proposed methodology, this can be concluded that "the combination of more than two classifiers can give better accuracy than single flat classifier".

Table 3. Comparison of results with other methods

Sr.No.	**Methods**	**Accuracy in Percentage**
1	**Proposed Hierarchical SVM**	**96.71**
2	Standard Flat SVM	82.69
3	Image Matching technique [12]	85.3
4	ANN Model [11]	83.75
5	Traditional Forensic Method	75% to 92% (Results vary from one Medical practitioner to another)

The combined L1-SVM + L2-SVM classifiers with features selected have given the maximum average accuracy of 96.71% for identification of the wound patterns and their weapons in comparison with the standard identification of flat SVM given high accuracy of 82.69%, as flat SVM for multiclass will not perform effectively. The comparison of both approaches with the performance parameters is as shown in Fig.7, Table 2 and Table 3. Both methods are tested for the same set of testing database, the performance of the hierarchical model has performed better compared flat model and other models. Based on the survey, it has shown that the identification by traditional method gives a lot of variation in the result i.e., 75% to 92%, this variation is because of forensic expert knowledge, experience in the field and other disadvantages mentioned in the introduction section.



(a) (b)

Fig. 7. (a) Accuracy comparison graph (b) ROC graph of standard flat and proposed hierarchical SVM

5. Conclusion

In this work, the performance of two approaches flat classifier and hierarchical structure are evaluated for the identification of four wound patterns and its weapons of cause in this framework. The hierarchical SVM classifiers gave remarkable and better results in comparison with flat SVM and traditional methods. The method (L1-SVM + L2-SVM) significantly improved performance and classification accuracy for all the classes and considerable reduction in errors due to distributed dissimilarities between wound patterns as compared with flat SVM classifiers obtained less accuracy compared to proposed method. It is observed that unlike most learning techniques, SVM can be trained even for the number of samples is much lower than input space dimensionality. The use of size, shape and textural features combination produced results that are more accurate in comparison with individual features, that shows textural features has minimum influence in the overall performance of classification. Hence, the selection of features and classifier for model interpretation requires a well-balanced factor between computational resources and accuracy of mapping. Finally, the result and performance obtained from the proposed methodology are efficient, acceptable and effective. The future work of the methodology is to consider a database that includes more different wounds images of weapons and to establish ultimately a classifier that performs effectively and efficiently, that brings the data explosion problem at the same time and to check how the hierarchical structure SVM will behave.

References

[1] Anil Jain and Jung-Eun Lee, (2009), *"Scars, marks, and tattoos: soft biometrics for identifying suspects and victims"*, Journal of SPIE, the international society for optics and photonics, pp: 01-02

[2] B.S.Anami, D.G.Savakar, (2009), *"Effect of Foreign Bodies on Classification and Classification of Bulk Food Grains Image Samples"*, Journal of Applied Computer Science and Mathematics, Vol.3(6), pp: 77- 83.

[3] Song Bo, (2012) "Automated wound classification system based on image segmentation and Artificial Neural Networks", IEEE International Conference on Bioinformatics and Biomedicine, pp: 11-16.

[4] Li Dongguang, (2008) *"Firearm Classification System Based on Ballistics Image Processing"*, Proceedings of CISP '08, Congress on Image and Signal Processing Vol: 3, pp: 149 – 154

[5] Li Dongguang, (2008) *"Firearm Classification System Based on Ballistics Image Processing"*, Proceedings of CISP '08, Congress on Image and Signal Processing Vol: 3, pp: 149 – 154

[6] Suapang P., Rangsit, et.al., (2011), *"Tool and Firearm Classification System Based on Image Processing"*, Proceedings-11th International Conference on Control, Automation and Systems (ICCAS), pp: 178 – 182

[7] Francisco Veredas, Héctor Mesa, and Laura Morente, (2010)*" Binary Tissue Classification on Wound Images With Neural Networks and Bayesian Classifiers"*, IEEE transactions on medical imaging, Vol: 29, Issue No. 2, pp: 410-426.

[8] Jie Liu1, Jigui Sun, Shengsheng Wang, (2006) "*Pattern Classification: An overview*", IJCSNS International Journal of Computer Science and Network Security, Vol:6, Issue No.6, pp: 57-61

[9] Qi Peter Li, and Biing-Hwang Juang, (2006) *"Study of a Fast-Discriminative Training Algorithm for Pattern Classification"*, IEEE transactions on neural networks, Vol: 17, Issue No. 5, pp-1212-1221

[10] Dayanand G Savakar, Anil Kannur (2015) "A Genetic algorithm and Bayesian approach for classification & classification of weapon based on the stab wound patterns caused by different sharp metal", International Journal of Computer Engineering and Applications, Volume IX, Issue I, pp: 01-12.

[11] Ajay Kumar N, ChenyeWu, (2011) "Automated human classification using ear imaging", Journal of Pattern Classification, Elsevier Ltd., pp: 1-13.

[12] Shuaibur Rahman, M. N. A. Khan, (2016) "*Digital Forensics through Application Behavior Analysis*", International Journal of Modern Education and Computer Science, Vol.8, No.6, pp.50-56.

[13] Rubayyi Alghamdi, et.al., (2016) "*Hidden Markov Models (HMM) and Security Applications*", International Journal of Advanced Computer Science and Applications, Vol. 7, Issue 2, pp:39-47.

[14] Gitto L., Vullo A., Demari G.M., (2012) *"Classification of the murder weapon by the analysis of a typical pattern of sharp force injury"*, Italian Journal of Legal Medicine, Vol: 01, Issue No. 1, pp: 04-14.

[15] Ying Bai; Dali Wang, (2011)*"Evaluate and identify optimal weapon systems using fuzzy multiple criteria decision making"*, Proceedings of IEEE International Conference on Fuzzy Systems, pp: 1510-1515.

[16] F.A. Andaló, A.V. Miranda, A.X.Falcão, (2009)," *Shape feature extraction and description based on a tensor scale"*, Journal of Pattern Classification, Elsevier Ltd, pp:1-11.

[17] Basavaraj S. Anami and Dayanand G. Savakar, (2011), *"Suitability of Feature Extraction Methods in Classification and Classification of Grains, Fruits and Flowers"*, International Journal of Food Engineering, Vol.7, Issue 1, Article 9, pp: 1-28, Publisher: Berkeley Electronic Press, Berkeley, U.S.A.

[18] Ying Bai; Dali Wang, (2011)*"Evaluate and identify optimal weapon systems using fuzzy multiple criteria decision making"*, Proceedings of IEEE International Conference on Fuzzy Systems, pp: 1510-1515.

[19] Kaliszan M., Karnecki K., Akçan R., (2011) "Striated abrasions from a knife with a non-serrated blade—classification of the instrument of crime on the basis of an experiment with material evidence", International Journal of Legal Medicine, Vol: 125, Issue No. 5, pp: 745–748

[20] Kaliszan M., Karnecki K., Akçan R., (2011) "Striated abrasions from a knife with a non-serrated blade—classification of the instrument of crime on the basis of an experiment with material evidence", International Journal of Legal Medicine, Vol: 125, Issue No. 5, pp: 745–748

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