

# **BULLET CLASSIFICATION SYSTEM BASED ON IMAGE IMAGE PROCESSING & SUPPORT VECTOR MACHINE**

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## **ABSTRACT**

*Our study suggests a strong svm for bullet image categorization, which solves the issues related to too many parameters. Throught the rigorous learning phase, the gap among points related to data and the center of cluster is used to compute the better metric. The implementation of the appropriate pocedures to the suitable SVM learning builds the decision function not much degraded with outliers, and coordinates the amount of synchronisation implicitly. Studies for the bullet classification system based on image processing and svm. This study shows that total number of svms are reduced and also enhances precision compared to classical SVM training.*

**Keywords:** *Image categorization, training support vectors, classification of objects.*

## **I. INTRODUCTION**

Bullet recognition and authentication, which is related to image processing, is modern research. The inspiration for this work is to construct a method for implicitly identifying and authenticating bullets in variety of scenarios. The bullets property checkup is very essential to be performed in the manufacturing of bullets before market release. Defense industry is progressively advanced, particularly in the area of artillery. Quantity and quality of bullets is very important in artillery, as even smallest variation can be certainly unsafe while it is expended. Consequently, the bullet property verification is very crucial. In the case of one time production, it is required to build a system, which explicitly identify defects in bullets. Image processing methodologies can be applied to identify defects in bullets as it is successfully applied on metallic surfaces.

The suggested procedure is related to categorization of bullet hole images. SVM is used for classifying images linearly and non linearly. In this study, we have designed an algorithm known specific support vector machine algorithm, which is useful for detecting holes in the bullets. In recent time SVMs shown excellent performance in the detection of hand written digit identification, image categorization [1], object authentication [2], face authentication [3], text classification [4] and prediction [5].

The suggested procedure is employed to the categorization of holes in the bullet images .The research outcomes exhibits that number vectors in standard SVM are reduced drastically. SVMs are accepted procedure in the area of machine learning algorithms as the SVM algorithm implemented logically and also deliver decent generalization abilities in its application. In this paper, categorization of images related to bullets by applying

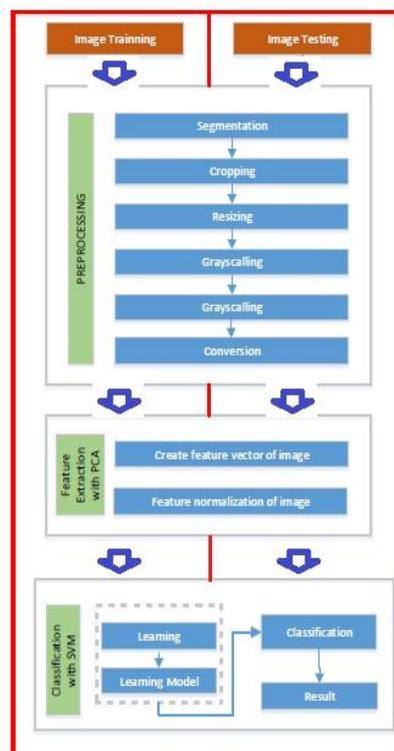
SVMs has been executed. This categorization will differentiate among images with deficiency and without deficiency.

## 2. Procedure

Figure 1 displays the structure of the categorization procedure images of bullets by applying SVM. Categorization procedure contains of numerous phases: bullet image scanning phase, pre-processing phase, attribute extraction phase and categorization phase. The input to the designed system is color bullet images. In the phase of pre-processing color bullet images are fed to the system, which is designed

**Table 1: Categorization Outcomes since Incidence Count illustration for bullet Measure using Standard dataset**

|                  | ACMC | ICIS | NCRA | DME | Label       |
|------------------|------|------|------|-----|-------------|
| <b>B Sample1</b> | 12   | 27   | 189  | 60  | <b>ACMC</b> |
| <b>B Sample2</b> | 179  | 64   | 9    | 24  | <b>NCRA</b> |
| <b>B Sample3</b> | 5    | 104  | 0    | 12  | <b>NCRA</b> |
| <b>B Sample4</b> | 3    | 5    | 2    | 104 | <b>NCRA</b> |
| <b>B Sample5</b> | 12   | 60   | 12   | 27  | <b>ICIS</b> |
| <b>B Sample6</b> | 179  | 24   | 179  | 64  | <b>NCRA</b> |
| <b>B Sample7</b> | 5    | 12   | 5    | 104 | <b>DME</b>  |
| <b>B Sample1</b> | 3    | 104  | 3    | 5   | <b>DME</b>  |
| <b>B Sample1</b> | 12   | 60   | 12   | 27  | <b>DME</b>  |
| <b>B Sample1</b> | 179  | 24   | 12   | 64  | <b>ACMC</b> |



**Figure 1. System of the categorization Organization**

Founded on overhead instructions for three bullets, by separate descriptors education remained transmit out to examination in what way it will be the consequence. Two pigment descriptors, two surface descriptors, and two contour descriptors remained secondhand separately to check the ability of recognition of animals. The results gathered are summarized in **Table 1**.

2300 of positive images of tigers 960 of negative images like other bullet image sequence, bullet samples and etc. and 422 of bullets of challenging remained rummage-sale. 456 of progressive descriptions of bullets 875 adverse imageries

| <b>Traditional Set</b>             |                        |                |                |                |
|------------------------------------|------------------------|----------------|----------------|----------------|
| <b>Random Generation</b>           | <b>Sample1</b>         | <b>Sample2</b> | <b>Sample3</b> | <b>Sample4</b> |
|                                    | <b>Frequency Count</b> | 0.73           | 0.45           | 0.654          |
|                                    | <b>TFID</b>            | 0.540          | 0.513          | 0.6256         |
| <b>Farthest Neighbor Technique</b> | <b>NCRA</b>            | <b>NCRA</b>    | <b>DME</b>     | <b>PCC</b>     |
|                                    | <b>ACMC</b>            | 0.415          | 0.538          | 0.5317         |
|                                    | <b>NCRA</b>            | 0.335          | 0.3223         | 0.473          |
| <b>Nearest Neighbor Technique</b>  |                        | <b>DME</b>     | <b>NCRA</b>    | <b>PCC</b>     |
|                                    | <b>Frequency Count</b> | 0.425          | 0.654          | 0.482          |
|                                    | <b>TF-IDF</b>          | 0.337          | 0.542          | 0.461          |
| <b>Reuter's Data Set</b>           | <b>DME</b>             | <b>ACMC</b>    | <b>CPP</b>     | <b>TF-IDF</b>  |
| <b>Random Generation</b>           |                        | <b>ACMC</b>    | <b>DME</b>     | <b>PCC</b>     |
|                                    | <b>Frequency Count</b> | 0.5285         | 0.538          | 0.531          |
|                                    | <b>TF-IDF</b>          | 0.4509         | 0.4737         | 0.588          |
| <b>Farthest Neighbor Technique</b> |                        | <b>DME</b>     | <b>DME</b>     | <b>PCC</b>     |
|                                    | <b>Frequency Count</b> | 0.527          | 0.5376         | 0.5337         |
|                                    | <b>TF-IDF</b>          | 0.475          | 0.473          | 0.5872         |
| <b>ACMC</b>                        |                        | <b>CCP</b>     | <b>CCP</b>     | <b>PCC</b>     |
|                                    | <b>NCRA</b>            | 0.405          | 0.876          | 0.442          |
|                                    | <b>TF-IDF</b>          | 0.343          | 0.543          | 0.432          |

**Table 2: Entropy Outcomes for different procedures by dissimilar methods**

## V. CONCLUSION

This document offers a overall vigorous SVM procedure anti outliers. By addition the coldness amongst each data point and the focus of modules to form the border of unraveling hyper plane, upright vigorous routine is reached. The replication of robust SVM with different kernel functions and regularization variables has been

obtainable to demonstration that the healthy procedure can be used for pattern classification problems with different difficulty levels. The experiment results show that the decision border becomes less detoured and the number of support vectors of the robust SVM is reduced meaningfully associated to that of the average SVM. Consequently, simplification presentation of the vigorous SVM is got as exposed in the imitation.

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