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Maritime Surveillance with Planes Using Machine Learning Techniques

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ABSTRACT

Maritime surveillance has great importance for the security and prevention of threats to any nation. In this manuscript, the proposed scheme, the problem of exploration, security and surveillance is assumed to be performed by advanced surveillance planes and/or helicopters on the seas through advanced radar and imagery is discussed. The proposed solution targets to building an effective classification model when the high dimensional data is given that is taken from radar signals is a major challenge to solve this problem for automatic target recognition community (ATR). The problem is severed when images have taken from different azimuth angles. To surmount this classification problem and high dimensionality issues in the dataset, we propose a framework that comprises of Principal Component Analysis (PCA), which are used for feature extraction, as well as feature ranker of data. This framework is developed using Python language and various Python packages. PCA features are used to train SVM, KNN and NB classifiers. Test data results are analysed corresponding to each model. Then, the performance of the proposed framework is evaluated and found that the accuracy levels are high from 89-94% corresponding to machine learning classifiers and SVM model outperformed in comparison to KNN and NB models and overall this research work is yielding better results other existing methods.

Key words: Feature Extraction, Maritime, Surveillance, Radar Signals, ATR, PCA, machine learning

1. INTRODUCTION

Maritime surveillance operations have become necessity of these days for greater security and prevention of threats. To overcome the inherent challenges imposed to recognise the relevant target, many researchers work in this direction. Generally, maritime surveillance is done by the on-board planes and helicopter, as shown in Figure 1. These vehicles use advance radar and high-resolution imagery for the purpose of identification of suspicious targets. But the dependency remains on the observer to correctly recognize the objects. This method leads to slow procedure. To overcome the dependency on the observer and speedup the task, automation of this procedure is required.
Various methods are used for automatic target recognition (ATR) from synthetic aperture radar (SAR) data which is clearly suggested in the literature. For soaring resolution radar images, ground based object recognition based on high resolution images taken from the synthetic aperture radar installed on airborne vehicles is a problem for manual detection and identification of the appropriate targets. After the inclusion of consecutive radar signal reflections, electrical signal image processing techniques are typically used to produce descriptive images. In adverse weather conditions and where the optical camera is of no use, ground photos may be equipped. Figure 2 represents the schematic of synthetic aperture radar.
Their performances are described under training and testing scenarios with sample data. The comparative performance of different methods can be unmanageable to measure these empiric ratings. The existence of this problem is due to execution points which vary from the one particular information to other particular information which may or may not achieve optimal results in the study to which it is implemented.

Figure 1: Maritime Surveillance with Planes

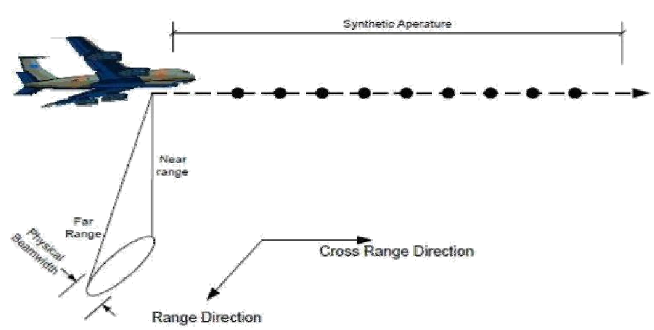

Figure 2: Synthetic aperture radar

2. RELATED WORK

For this matter, we collected lot of different articles which provide details for many views of ATR. We start by concentrating on polari-metric synthetic aperture radar imagery and the methods used to discover, separate and classify targets found in such imagery.

A general summary of classical pattern recognition approach is proposed by authors of [1-2]. The author [3] speaks about the issue of distinguishing targets from natural clutter artefacts that provide evidence of radar energy to pass through the sensing point. Article [4] deals more or less with the difficulties of separating three dimensional targets from their two dimensional SAR signatures, and formulates a framework for the classification process to include three dimensional details.

The authors address the subject of neural network recognition schemes in [5-6]. It discusses about certain motivations of neural network architectures that are derived from biological image recognition. These neural processing principles are discussed on a variety of separate objective perception topics.

A description of laser radar imagery is given by the authors [7-9], and at the same period captures reflection and range details. This paper also concerns with the challenge of computing algorithms for ATR. The growth of an electronic terrain board for checking and measuring ATR algorithms may be more cost effective due to the cost of collecting training and research imagery covering the severity of current ATR scenarios.

The author [10] speaks over the use of neural networks for laser radar imaging to apply an image enhancement algorithm to Markova random fields. The effect on the output of the target classifier of this pre-processing tread is defined.

In [11], the author explains the use of target detection laser radar measurements, but the authors use a model based methodology. Signal identification has been carried out by several algorithms running in parallel and using a process called functional prototype correlation to scan for many image properties. Target data is taken down to attributes that fit preserved presentation prototypes. On training results, the weights used to control the subsequent process could be discovered adaptively.

3. METHODOLOGY

In this manuscript, the proposed method is used to solve the problem related to recognition of (ground) objects or one of the primary applications of this paper is to solve the real-world problem. For example, suppose there is a war going between countries or enemies who are searched for in critical duration viz important artilleries and weapons. The basic problem is how to accomplish this task as shown in figure 3.

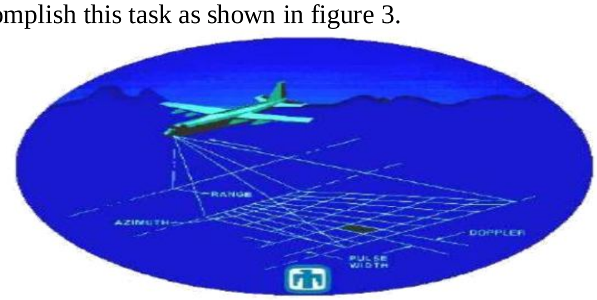

Figure 3: Illustration of SAR geometry and automatic target data collection scheme

In this article, researchers use the method of PCA for feature extraction to solve such a type of problem and to characterise the artefacts on the basis of their related characteristics. One of the most notable observations from integrated linear algebra is the PCA. It is extravagantly used in all groups of neuro-science to computer graphics review. Due to its simplicity, non parametric method of drawing out applicable information from disconcerting data sets. PCA provides instructions for reducing composite data to a lower dimension with a minimum extra attempt to divulge masked, altered kinetics that often from the basis for it. The extraction of features begins with the start of a collection of calculated data and generates derived values for the field of machine learning, image processing and pattern recognition which will aid the following learning and generalization steps and often lead to improved human interpretations. It is also related to reducing dimensionality. It can be modified into a reduced collection of features when the input data to an algorithm is broad to be processed and distributed to be redundant. This is known as feature selection and the pseudo code of PCA is summarized in Algorithm 1.

```
R ← X
for(k = 0, ..., K − 1) do
    {
    λ = 0
    T^(k) ← R^(k)
    for(j = 0, ..., J) do
        {
        P^(k) ← R^T T^(k)
        P^(k) ← P^(k) ||P^(k)||^(−1)
        T^(k) ← R P^(k)
        λ' ← ||T^(k)||
        if(|λ' − λ| ≤ ε) then break
        λ ← λ'
        }
    R ← R − T^(k) (P^(k))^T
    }
return T, P, R
```

Algorithm 1: Pseudo code of PCA

So, in this current work to extract the features from the SAR images PCA technique is used. In addition to that team used machine learning algorithms. The algorithms used as classifier here are as follows

i. Naive Baye's :

Naive Baye's is the barest example to develop a identical compress delicacy of a high dimensional probability distribution. We have a class variable A that accepts values in some set$\{A^1,...,A^k\}$.The model also adds more or less number of features $\{C_{1,} \,..._{..} C_n\}$ of which values are typically found. The author [12] explains the NB in detail. The pseudo code of Naïve Baye's is summarized in following steps.

ii. Support Vector Machine (SVM)

SVM supporting devices are focused o decision making aircraft that determine decision limits. A decision plane divides a variety of objects from distinct class memberships. The SVM facilitates both regression and classification activities and is capable of managing several categorical and continuous variables [13]. It can obtain the unique optimal solution. The pseudo code of SVM is summarized in following steps.

INPUT: training set T, hold-out set H, initial number of components k_o, and convergence thresholds δ_{EM} and δ_{Add}.
Initialize M with one component.
K <---- k_o
repeat
Add k new mixture components to M, initialized using k random examples from T.
Remove the k initialization examples from T.
repeat
E-step: Fractionally assign examples in T to mixture components, using M.
M-step: Compute maximum likelihood parameters for M, using the filled-in data.
If log P (H\M) is best so far, save M in M_{beat}.
Every 5 cycles, prune low-weight components of M.
until log P (H\M) fails to improve by ratio δ_{EM}.
M <---- M_{beat}
Prune low weight components of M.
K <---- 2k
until log P (H\M) fails to improve by ratio δ_{Add}.
Execute E-step and M-step twice more on M_{beat}, using examples from both H and T.
Return M_{beat}.

Algorithm 2: Pseudo code of Naive Baye's

Let W = {$x_1, x_2, \ldots, x_n$} be a set of n labeled samples. The algorithm is as follows:
BEGIN
Input y, of unknown classification.
Set K, 1 < K < n.
Initialize i = 1.
DO UNTIL (K-nearest neighbors found)
Compute distance from y to x_i.
IF (i < K) THEN
Include x_i in the set of K-nearest neighbors
ELSE IF (x_i is closer to y than any previous nearest neighbor) THEN
Delete farthest in the set of K-nearest neighbors
Include x_i in the set of K-nearest neighbors.
END IF
Increment i.
END DO UNTIL
Determine the majority class represented in the set of K- nearest neighbors.
IF (a tie exists) THEN
Compute sum of distances of neighbors in each class which tied.
IF (no tie occurs) THEN
Classify y in the class of minimum sum
ELSE
Classify y in the class of last minimum found.
END IF
ELSE
Classify y in the majority class.
END IF
END

Algorithm 3: Pseudo code of KNN

iii. K-Nearest Neighbour (KNN):

The KNN algorithm is a non-parametric approach for classification and regression used in the area of machine learning and pattern recognition. Defer the decision to generalize beyond the training examples till a new query is encountered. Whenever we have a new point to classify, we find its K- nearest neighbours from the training data. Actually the distance is calculated using Euclidean Distance. The pseudo code of KNN is summarized in following steps.

INPUT: S, λ, T, k
INITIALIZE: Choose w_1 s.t. $\|w_1\| \leq 1/\sqrt{\lambda}$
FOR $t = 1, 2, \ldots, T$
Choose $A_t \subseteq S$, where $|A_t| = k$
Set $A_t^+ = \{(x, y) \in A_t : y \langle w_t, x \rangle < 1\}$
Set $\eta_t = \frac{1}{\lambda t}$
Set $w_{t+\frac{1}{2}} = (1 - \eta_t \lambda) w_t + \frac{\eta_t}{k} \sum_{(x,y) \in A_t^+} y x$
Set $w_{t+1} = \min \left\{ 1, \frac{1/\sqrt{\lambda}}{\|w_{t+\frac{1}{2}}\|} \right\} w_{t+\frac{1}{2}}$
OUTPUT: w_{T+1}

Algorithm 4: Pseudo code of SVM

4. PROPOSED FRAMEWORK

The working methodology of work is diagrammatically shown in Figure 4a & 4b. As we see that there are three phases to solve the problem under discussion which are as follows [14]:

1) Preprocessing phase
2) Feature Extraction phase
3) Classification phase

We have taken image as input in the pre-processing stage and we have rendered image matrix from this image pixels, by doing this we get vectored image, and we try to imply the vectored image data which is oriented. This is called mean centering and from this data, we now construct a covariance matrix. Then we use another two phase's feature extraction and feature selection is shown in Figure 6-7 and classification phase is shown in Figure 8. In the training data collection, each image clip is from the same elevation but from a different angle of azimuth. Pixels of photographs are thought to be variables, taking azimuth angle adjustment as opposed to observations. The PCA is introduced in the data collection to minimize the number of variables found. Feature extraction using PCA is shown in Figure 4b.

5. EXPERIMENTAL RESULTS AND DATASETS

We select two datasets and apply relevant machine learning algorithms for classification purposes to validate our feature extraction process. We can quickly classify our land targets after the execution of algorithms and can even differentiate between the various types of vehicles. The datasets used are given in table 1.

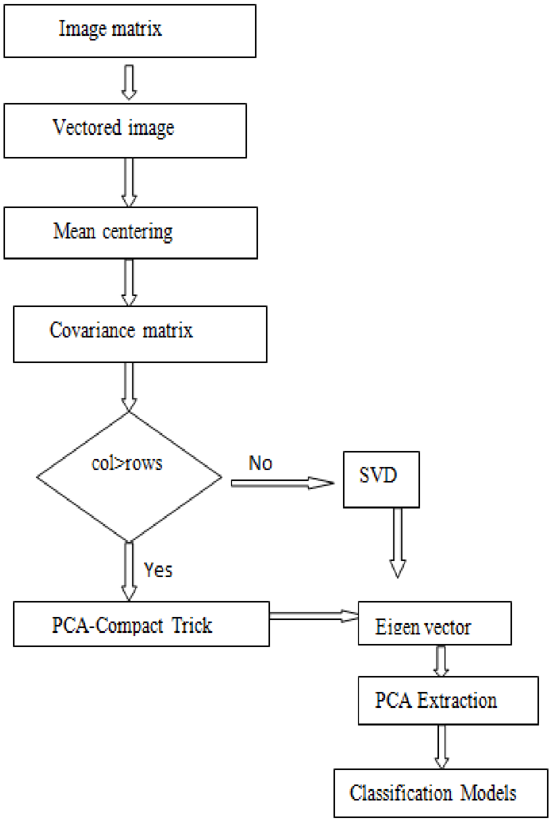

Figure 4a: Flow chart of PCA

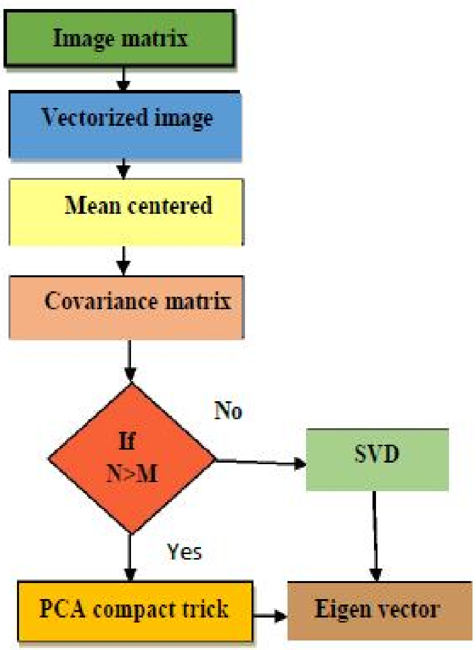

Figure 4b: Feature extraction using PCA

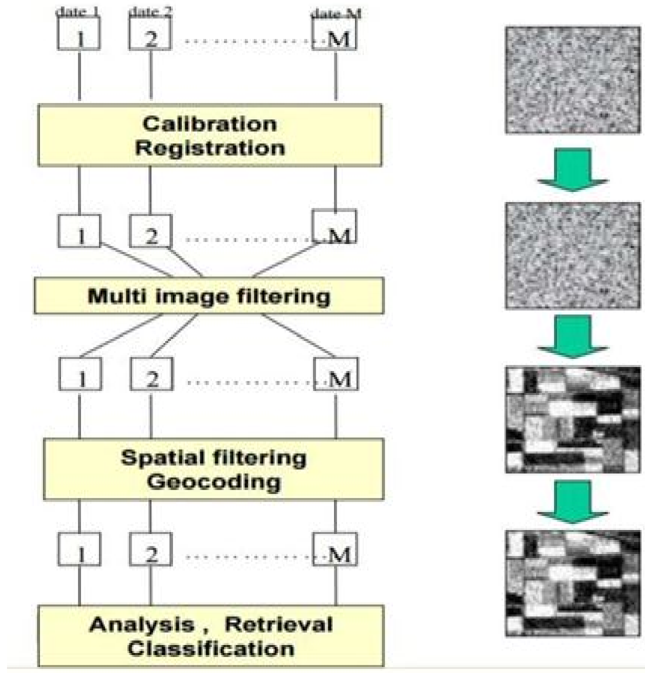

Figure 5: Pre-processing phase

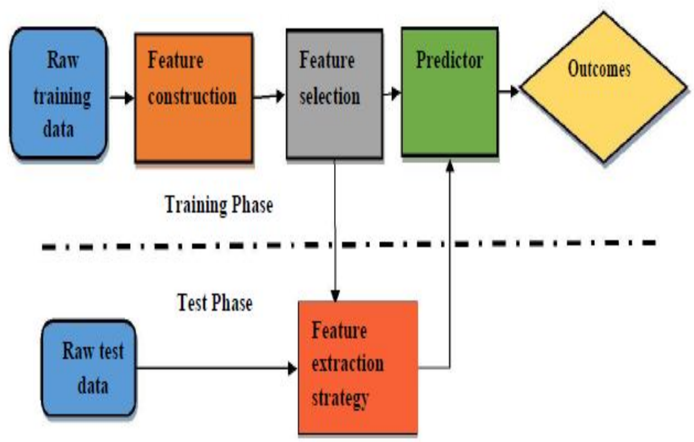

Figure 6: Phase of training and testing

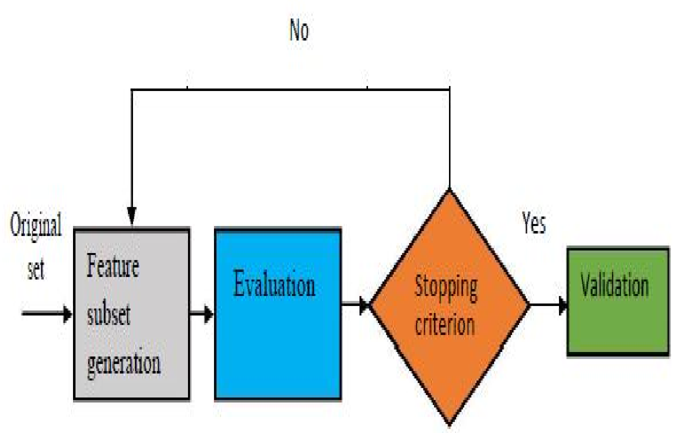

Figure 7: Feature selection procedures

Table 1: Summary of datasets used in experiments

Dataset Name	Samples	Features
BTR60	660	195
BRDM2	850	273
Random Samples	120	209
Mixed Dataset	120	188

An experimental result of proposed framework is presented below as Figure 8 and Table 2 used for the discussion on the working of classification phase.

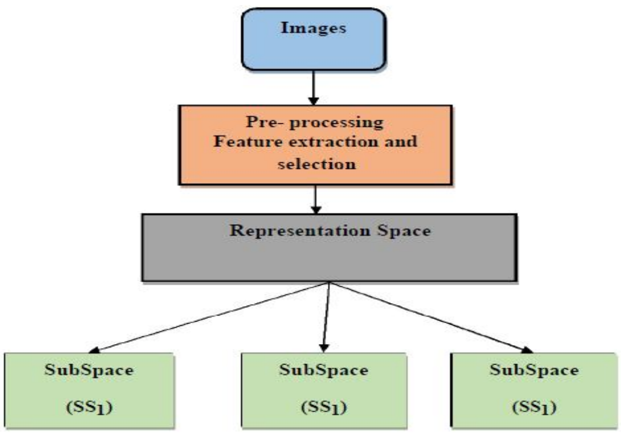

Figure 8: Classification phase

Binary classifiers model are developed and trained for each data set corresponding to all three classifiers as mention in section 4 are the standard metrics (precision (P), Recall (R), Accuracy (A) and F1-measure) are used access the proposed framework and trained models corresponding to the three popular classifiers. The cross validation accuracy and test dataset accuracy are also presented to check and compare the performance NB, KNN and SVM classifier algorithms on the Table1 datasets. This further helped to decide PCA generated features can be better utilized with which classifier. All of this will improve the confidence in the proposed technique.

SVM, KNN, NB model is trained by varying various parameters and kernel functions to get the highest accuracy. Standard five-fold validation technique is applied to obtain maximum cross validation (CV) accuracy to further test the model.

Table 2: Cross validation (CV) accuracy of classifiers for dataset BTR60

Classifier	Training Dataset-BTR60 CV Acc. %	Random Samples Data CV Acc. %
NB	93	88
KNN	88	84
SVM	97	92

As shown in Table 2 and figure 9 the maximum CV accuracy generated through NB is 93% in case of BTR60 data set and 88% in case of random samples dataset.

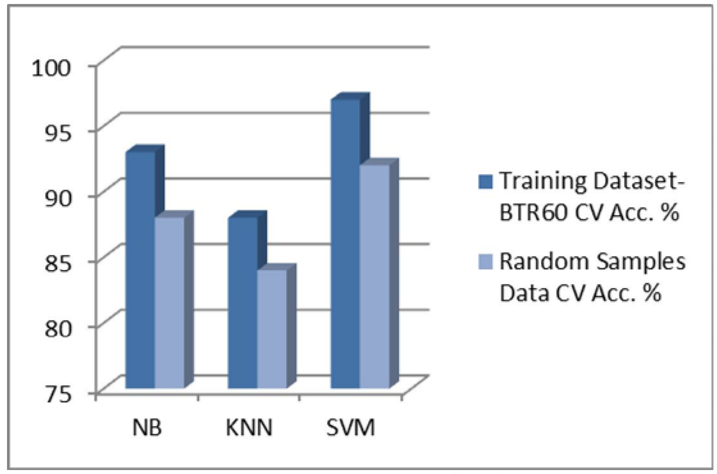

Figure 9: BTR60-Data vs. Random data

SVM model produced 97% and 92%. This is the highest among all model classifiers Whereas, KNN model was capable of yielding only 88% and 84% respectively and is lowest in both type of datasets.

Table 3: Cross validation (CV) accuracy of classifiers for dataset BRDM2

Classifier	Training Dataset-BRDM2 CV Acc.	Random Samples Data CV Acc.
NB	92	89
KNN	87	86
SVM	96	91

In case of BRDM2 dataset and Random samples dataset, the CV accuracy levels are shown in table 3 and figure 10. As indicated by table 3 CV accuracy values are NB 92% & 89%, KNN 87% & 86% and in case of SVM trained classifier are 96% & 91% again is highest among all.

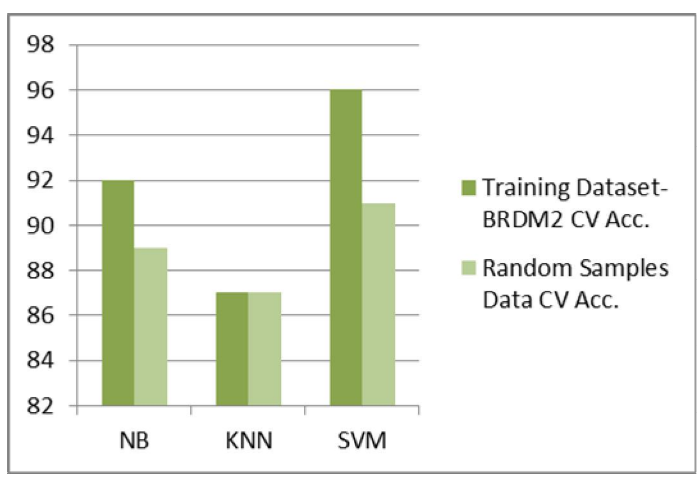

Figure 10: BRDM2-Data vs. Random data

Further test dataset corresponding to BTR60, BRDM2 and Random Samples (RS) are tested on all the trained classifiers to calculate various evaluation parameters such as Precision (P), Recall (R), Accuracy (A) and F1-measure metric. The value of these metrics helped in analyzing trained models based on Principle component analysis (PCA) feature sets.

Table 4: Precision (P), Recall(R), Accuracy (A) and F1 metric for dataset BTR60.

Domain/ Classifier	Test Dataset1- BTR60			
	P	R	A	F1
Naïve Baye's	0.88	0.82	87	0.84
KNN	0.89	0.78	88	0.83
SVM	0.93	0.92	92	0.92

Study of standard evaluation metrics helped in testing classifier models from various angles. As shown in table 4 and figure 11 NB classifier yield values of P, R, A and F1 as 0.88, 0.82, 87% and 0.84 respectively.

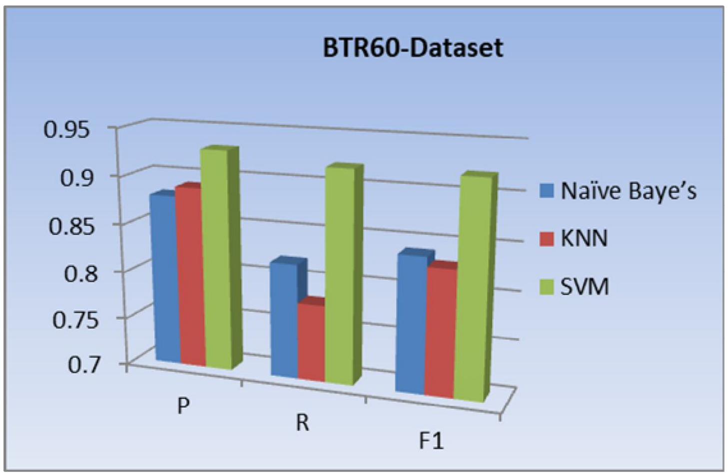

Figure 11: Test Data - (BTR60 Dataset)

In case of KNN model values are 0.89, 0.78, 88% and 0.83 respectively and in case of SVM these values are 0.93, 0.92, 92% and 0.92 respectively. So the highest accuracy levels could be obtained through SVM trained classifier.

Table 5: Precision (P), Recall(R), Accuracy (A) and F1 metric for dataset BRDM2.

Domain/ Classifier	Test Dataset2- BRDM2			
	P	R	A	F1
Naïve Baye's	0.86	0.81	88	0.83
KNN	0.86	0.79	86	0.82
SVM	0.94	0.91	93	0.92

Table 5 indicated corresponding evaluation metrics w.r.t BRDM2 dataset. As evident from the and figure 12 the highest

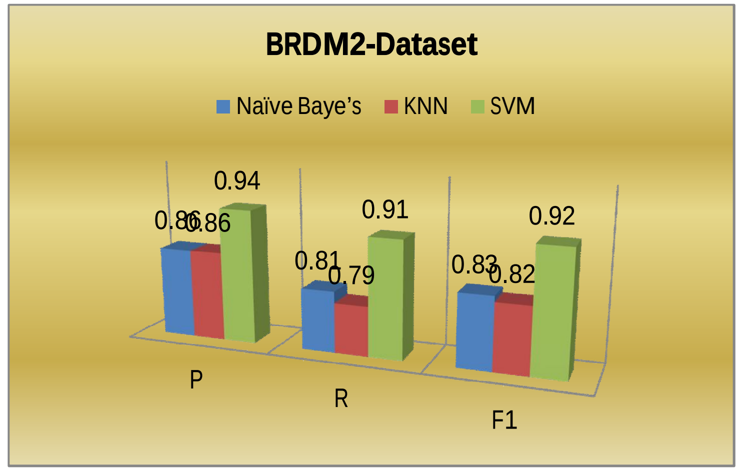

Figure 12: Test Data-(BRDM2 Dataset)

accuracy is obtained through SVM classifier with the values of P, R, A and F1 as 0.94, 0.91, 93% and 0.92 respectively.

Table 6: Precision (P), Recall(R), Accuracy (A) and F1 metric for dataset Random Samples**.**

Domain/ Classifier	Test Dataset3- Random Samples			
	P	R	A	F1
NB	0.82	0.78	87	0.79
KNN	0.83	0.79	92	0.80
SVM	0.87	0.83	88	0.84

As shown in table 6 and figure 13 Random Samples dataset is also tested corresponding to column 3 of table 3 and table 4 to generated metrics values to boost the confidence level.

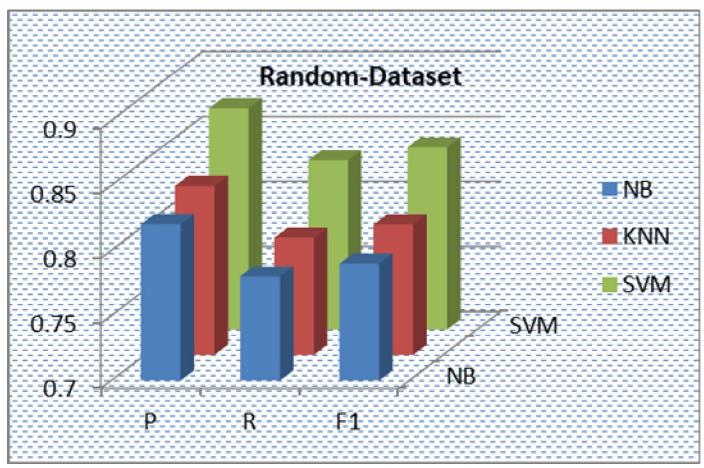

Figure 13: Test Data-(Random sample Dataset)

Again the values of P, R, A and F1 as 0.88, 0.82, 87% and 0.84 respectively in case of SVM classifier is higher as compare to NB (A) 92% and KNN (A) as 88%.

Table 7: Average Accuracy with different classifiers

Model Name	Average Accuracy (of data set 1 2,3)	Accuracy (Mix data set)
NB	89%	76%
KNN	86%	79%
SVM	94%	89%

Another analysis is done as shown in table 7 and figure 14 by applying the mixed dataset on already trained classifiers. Target class is changed each time corresponding to Random samples, BTR60 and BRDM2 datasets to get the average accuracy % corresponding to all the above classifiers and compare the performance by calculating the average accuracy % of each type of mentioned test datasets for SVM, KNN and NB trained model. It is evident from table 7 that SVM model average accuracy is higher i.e. 94 % and Mixed dataset average is 89%.

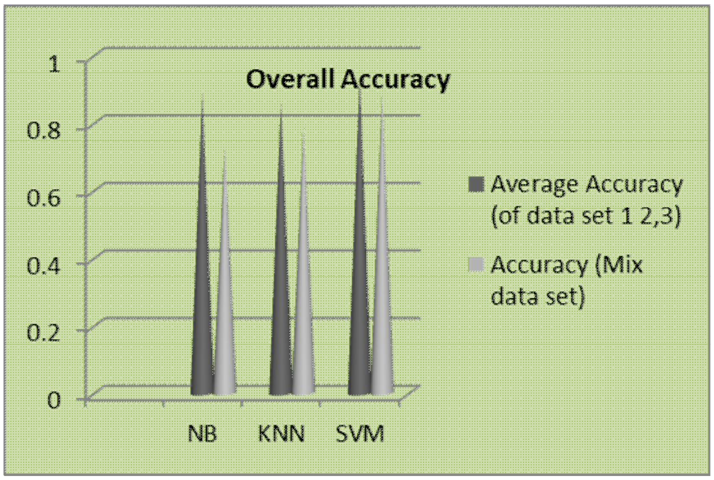

Figure 14: Model Accuracy
(Average of datasets vs. Mixed Dataset)

It is evident from the experimental results that the ship surveillance system for target recognition based on various classifiers is performing satisfactorily. SVM classifier outperformed the KNN and NB when single dataset is used to evaluate the accuracy of the proposed model. Accuracy score generated by SVM came out to be 94% whereas KNN produced 86% and NB classifier resulted in 89% accuracy level. In case of mixed data set KNN classifier lead to 79% accuracy whereas NB and SVM classifier could yield only 76% and 89%. Hence by analyzing the table 3, 4, 5, 6 and 7 the conclusion is drawn that the proposed work is satisfactory and it outperformed the results obtained by other similar research work as illustrated in the related work section Moreover, SVM classifier model best yield result with the features obtained through PCA technique.

6. CONCLUSION

To improve the further level of security and surveillance supposed to be performed by the marine ships and on-board aerial vehicles, an automatic target recognition system is mandatory. In this paper, a new framework is proposed, called PCA Compact trick (feature extraction). It is employed as a pre-processing and feature selection step to train NB, KNN and SVM on SAR image dataset. When compared with experimental results derived using PCA Compact trick which is used for feature extraction, it has been observed that the Support Vector Machine based trained classifier model outperformed the K-Nearest Neighbour and Naïve Baye's algorithms and. the classification of data can be improved significantly to key out the rare events from the datasets by applying computationally less expensive feature selection technique (PCA). During the analysis of the standard evaluation metrics obtained through experimental setup corresponding to various datasets, it is found that the proposed framework indicates promising results and finally, it is concluded that better performance, efficiency and accuracy is achieved through proposed work than other techniques.

7. FUTURE SCOPE

The proposed scheme's results are motivating and work will be extended further in this direction. In future multiclass classifier model will be developed to enhance the capabilities of surveillance system by supporting multiple class targets. Through this increment the multiple targets cloud be recognized quickly and easily. Moreover tracking of multiple targets simultaneously would be possible. In future deep learning approach may be applied to automatically identify the features and train the multiclass model. Further refinement may improve the accuracy and enhance the overall performance.

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