Performance Analysis of Detection of Video for Secured Cloud Data Service

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Abstract--- *Identifying malady could be critical to forestalling farming misfortunes. The objective of this paper is to make a Computer helped analysis to distinguish and classifies the video frame analysis. This proposed identification look into includes video frame image acquisition, pre-processing, segmentation, extraction, and classification stage. The outline of the video is utilized to frame conversion. Four stages are utilized to recognize Video. The initial step is preprocessing then segmentation utilized here is threshold dependent segmentation of the faster 2D-Otsu. The subsequent stage is the extraction of the functionality, utilizing the GLCM tool. The third stage is that of description. Here the classifier for multiclass support vector machines (SVM) is utilized. And the last step is encryption. Here Small Encryption Algorithm (TEA) technique is used to encrypt data. The end encrypted output will be stored in the cloud. This technique is used to characterize the frame image on the video. The simulations are applied on MATLAB. Results of the experiment show the proposed efficiency of the device as compared to other methods of detection.*

Keywords--- *Median Filter, Faster 2D-Otsu's Segmentation, GLCM Feature, Multiclass Support Vector Machine.*

I. INTRODUCTION

Multimedia oriented video frame image retrieval system can be analysis in different applications. Different techniques for video frame handling for recognizing are discussed about right now. Wenjiang Huang et al [1] proposed a spectral indicator for the identification of the disease in winter wheat. RELIEF-F algorithm were 86.5 %, 85.2 %, 81.6%, and 83.5 % respectively for stable and damaged leaves. Monica Jhuria et al [2] discussed the Back degradation is being used to modify training databases by weight; morphological feature gives better results than the other two features. They find three function vectors, namely, light, textures & morphology [2]. From these feature vectors morphology gives 90% correct result. Husin et al [3] proposed a capture the chili plant video image, Pre-processing is achieved with the Fourier filtering, edge detection, and morphological operations. Computer vision expands the framework for object recognition processing of images. Accuracy level degrades. The clearness of clustering with k-means is more reliable than other approaches. Threshold value varies with less detecting level.

The SGDM matrix is developed for both the texture statistics approximation but with low feature [5].R.Meena Prakash et al [6], explained system includes a framework KNN classifier used to identify disease of the plant root. Low access rate when compared SVM classifier.

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Aparajita et al[7], discussed a conventional method identifies disease based on external evaluations, automatic detection of late blight disease from the video images based on image processing. Adaptive thresholding is used to segment affected disease. Accuracy level degrades based on the assessment of visual identification. Segmentation levels affect accuracy. Accuracy range will be 80%. Wanjale et.al,[8] proposed inspiration behind crop identification and productivity, unhealthiness of plant video exploration and recognition the signs of diseases at the initial phase itself. Recognition of plant diseases along with some automated approach is useful as it reduces enormous observation effort in large farms. Recognition level not finds accurate level of the disease. R.P.Narmadha and G.Arulvadivu,[9] proposed Paddy disease which can be identified, and all parts of plants, such as the neck of the video and the node. This methodology was designed to eliminate automatic noise, human error. Maximize the time required to measure the paddy-video disease effect. Accuracy rate 80.4% and the error rate is high (19.6%) when compare to pervious methods.

Method is based on image processing, Images are segmented using K-means and the segmented images are passed through some kind of pretrained neural network with minimum detection as well as classification with accuracy of the diseases tested. Generates fast, automated, cheap and not accurate solutions based on image processing for such a function can be of great practical relevance. Anand R et al, [11] proposed principal objective of the proposed study is to diagnose brinjal video disease using image processing and artificial neural technique, uses k-mean for segmentation.

II. RESEARCH GAP IDENTIFIED

The old strategy Otsu shows the generally large however the item territory is little contrasted with the foundation region, the histogram never again displays bimodality. At that point the incorrect threshold determined by the strategy for Otsu brings about the blunder in segmentation. Results show that the yield for object segmentation is constrained by little object size, the little mean contrast among fore area and foundation pixels, the enormous variance of object pixel and foundation pixels, huge amounts of noise, and so on. To determine this we propose video frame detection depending on the multi-class SVM.

The proposed research relates to:

- **i.** The **Faster 2D-Otsu thresholding** performs well during segmenting low signal to noise images. Faster 2D-Otsu used two One-Dimensional Otsu algorithms. Whereas the existing methodology of segmentation focuses on grey images as in [13]. *(Astha Baxi, Hetal J. Vala in 2013).*
- **ii.** Advantage of utilizing **Multi-class SVM** execution and exactness to encourage the way toward picking the best technique for the farming region. Normally for multiclass SVM which is its capacity to sum up well even with a little dataset. Multiclass SVM uses its properties including the improvement strategies by combining other methods and algorithm such as a genetic algorithm whereas the current classifier can be characterized by just two classes as in [14]. *(Devale, Mulay, Snehal in 2010)*
- **iii.** Tiny Encryption Algorithm (TEA) block cipher is a prominent for its straightforwardness of portrayal and usage, commonly a couple of lines of code. When contrasted with pervious calculation TEA is more verified for encryption [15]. *(Saarinen, Markku-Juhani in 1998)*

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The association of this paper is given by the following segments: Section III the picture securing technique is described where the picture is gained. The preprocessing stage is done where the resizing, Conversion of color space alongside noise removing occurs, trailed by the Histogram Equalization and Segmentation including the new strategy for Proposed Segmentation of influenced zone in video followed by quicker 2D-Otsu. The subsequent stage of Classification is finished with Feature Extraction by GLCM extraction and the grouping done by multiclass support vector machines. The last stage is Encryption done by the Tiny Encryption Algorithm (TEA). Segment IV clarifies the outcome analysis and segment V gives a conclusion.

III. METHODOLOGY

The calculation for the proposed stream has the accompanying advances and the means are clarified as underneath. The picture processing stages are done utilizing various calculations. Three stages are utilized to characterize Video. The initial step is the segmentation, and the segmentation used here is the threshold dependent segmentation of the faster 2D-Otsu.The subsequent stage is the extraction of the functionality here, utilizing the GLCM instrument. What's more, the last stage is positioning. Here the classifier for multiclass support vector machines (SVM) is utilized.

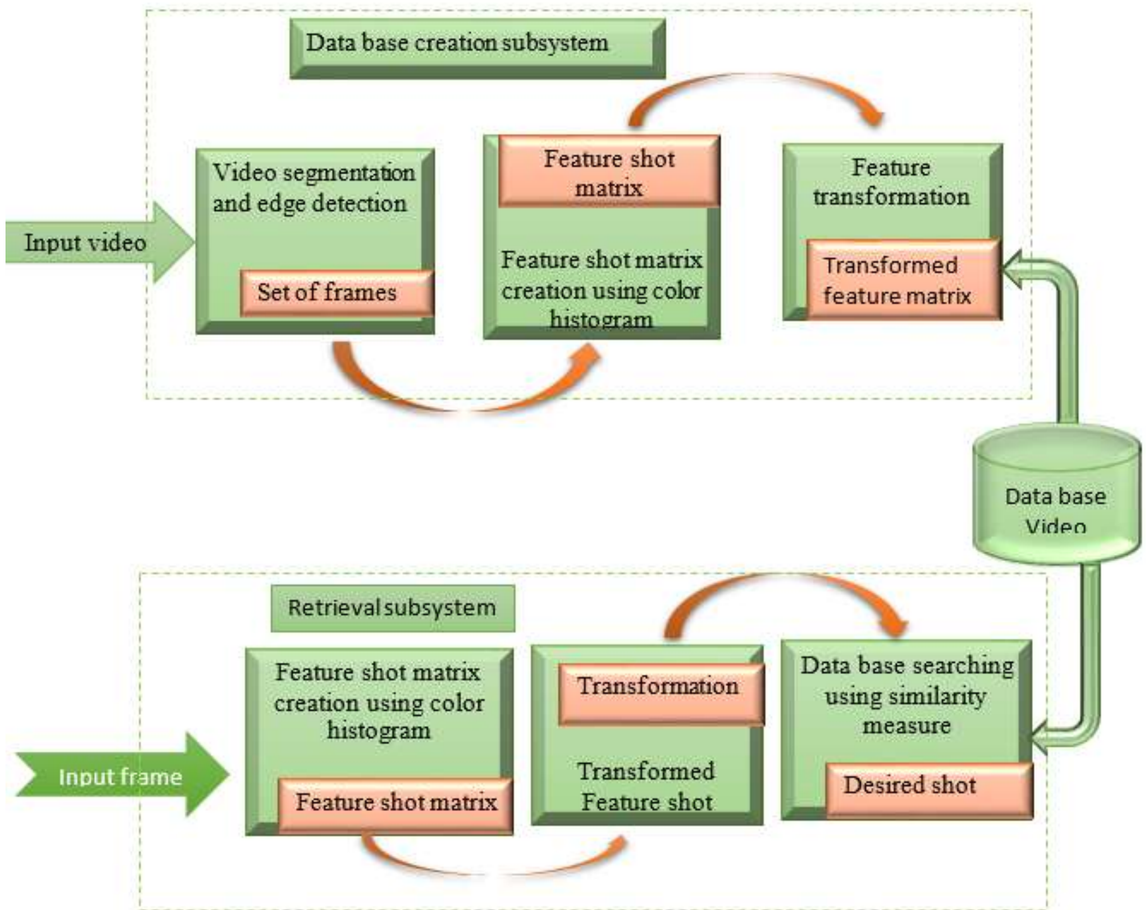

Figure 1: Proposed Flow Diagram of the System

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3.1 Image Acquisition

Image acquisition is by all accounts the initial step which includes a computerized camera to catch avideo. Pick the video that is influenced by the frame first, at that point gather the plant's video and take a video preview and load the videoframe into the program.

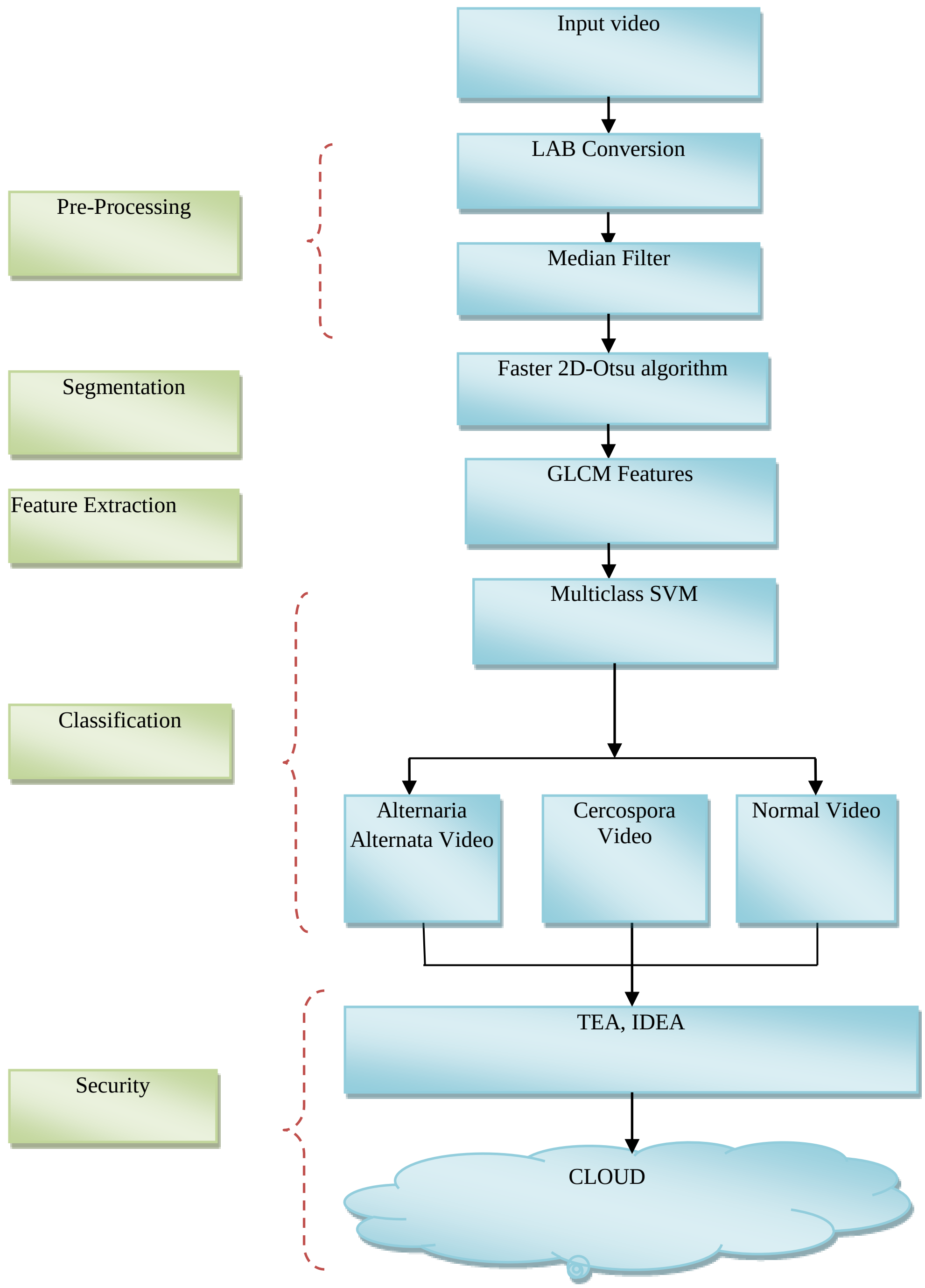

Figure 2: Proposed Flow Diagram

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3.2 Image Pre-Processing

The pre-preparing of video is utilized to improve the nature of the image required for considerably all the more processing and study. This joins the color space transfer and video upgrade. In the video catch, noise is constantly included. Utilize different sorts of filtration techniques to expel the commotion. The frame RGB pictures are changed over into color space L*a*b. The color change is intended to decide the reflectivity levels and chromaticity rates. Change of color space can be utilized to make a visual understanding of simpler Pre-processed pictures.

3.3 Image Segmentation

Image segmentation is the methodology used to enhance the portrayal of a video in, for instance, a noticeable structure to show object of enthusiasm from the context.2D Otsu segmentation in this suggested work.

Alongside the predetermined video frame, there are different foundations in the image of video after the noise decrease strategy, which will cause perplexity and reduction identification precision. To permit the recognizable proof and extension of informational indexes, we have to segregate the objective leaves from the unique circumstance, in particular the handling of picture segmentation. The Segmentation of the thresholds is progressively typical and simpler to perform.

The Otsu calculation proposed by the Japanese researcher Otsu in 1978 is known as the calculation of most extreme between class changes, which is one of the standard limit division strategy calculations with an exceptional division impact. By and by, the customary one-dimensional Otsu approach just perceives the picture's dark data however neglects to assess the picture's spatial subtleties. In this way, if the image histogram has no obvious twofold pinnacles, the loss of data will happen once the division approach is utilized.

However, considering the positive relationship between's certain target classes of the video disease and the interior pixels of the set class, this content thoroughly investigates between class change and intra-class difference and makes another new discriminating threshold mechanism. Calculation of proposed Otsu thresholding is depicted as follow:

Algorithm of Proposed Faster 2D OTSU thresholding

- ***Start the program***

$s_a = y_0 y_1 (v_0 - v_1)^2$ ***(1)***

Where v_0 and $v_1$simultaneously constitute the mean of the target class and the background class; $y_0$and $y_1$refer to the target and background class likelihood,

- ***Partition a single set of data into two groups, the variances of the two data types in the class are calculated***

$s_0 = \sum_{m=0}^{s} k_1 (i - v_0)^2$***(2)***

$s_1 = \sum_{m=s+1}^{L=1} k_1 (i - v_1)^2$***(3)***

k_1 Denotes the likelihood of occurrence of m, v_0 and v_1 including both the mean of the two types, andy_0,y_1 refers to two types of probability individually

$s_n = v_0 s_0 + v_1 s_1$***(4)***

$s_n$represents the cohesiveness of the two data types in this data category

- ***Determine the new discriminating feature***

$S = {}^{s_a}/_{s_n}$***(5)***

- ***Projecting the 2-D histogram***

$N = \left[\sqrt{2}(L-1)\right] x = \left[\frac{\sqrt{2}}{2}(i+j)\right]$ ***(6)***

$H(x) = \sum_{x=\left[\sqrt{2}(i+j)/2\right]} h(i,j)$ ***(7)***

- ***Find the line-p equation is summarized as follows.***

$g(x,y) = -f(x,y) + 2ii \in L(0,1,2,\ldots\ldots,L-1)$ ***(8)***

- ***Stop the program***

Canny Edge Detection Algorithm

Let S be the closed system.

S = {B, Xmin, Xmax, D}

Where, B = {b (i, j); i=1, 2,….M/m;

j=1, 2,…….N/n} -set of image blocks of size $m \times n$.

b (i, j) = original image block.

Xmin = {xmin (i, j);

i=1,2,….M/m; j=1,2,…..N/n} -set of minimum quantizer.

xmin (i, j) = minimum value over RGB color channels on corresponding image block (i, j).

Xmax = {xmax (i, j); i=1,2,….M/m; j=1,2,…..N/n} -set of maximum quantizer.

xmax (i, j) = minimum value over RGB color channels on corresponding image block (i, j).

D= {D0 , D1 ,…..,D255} -set of scaled version of dither array.

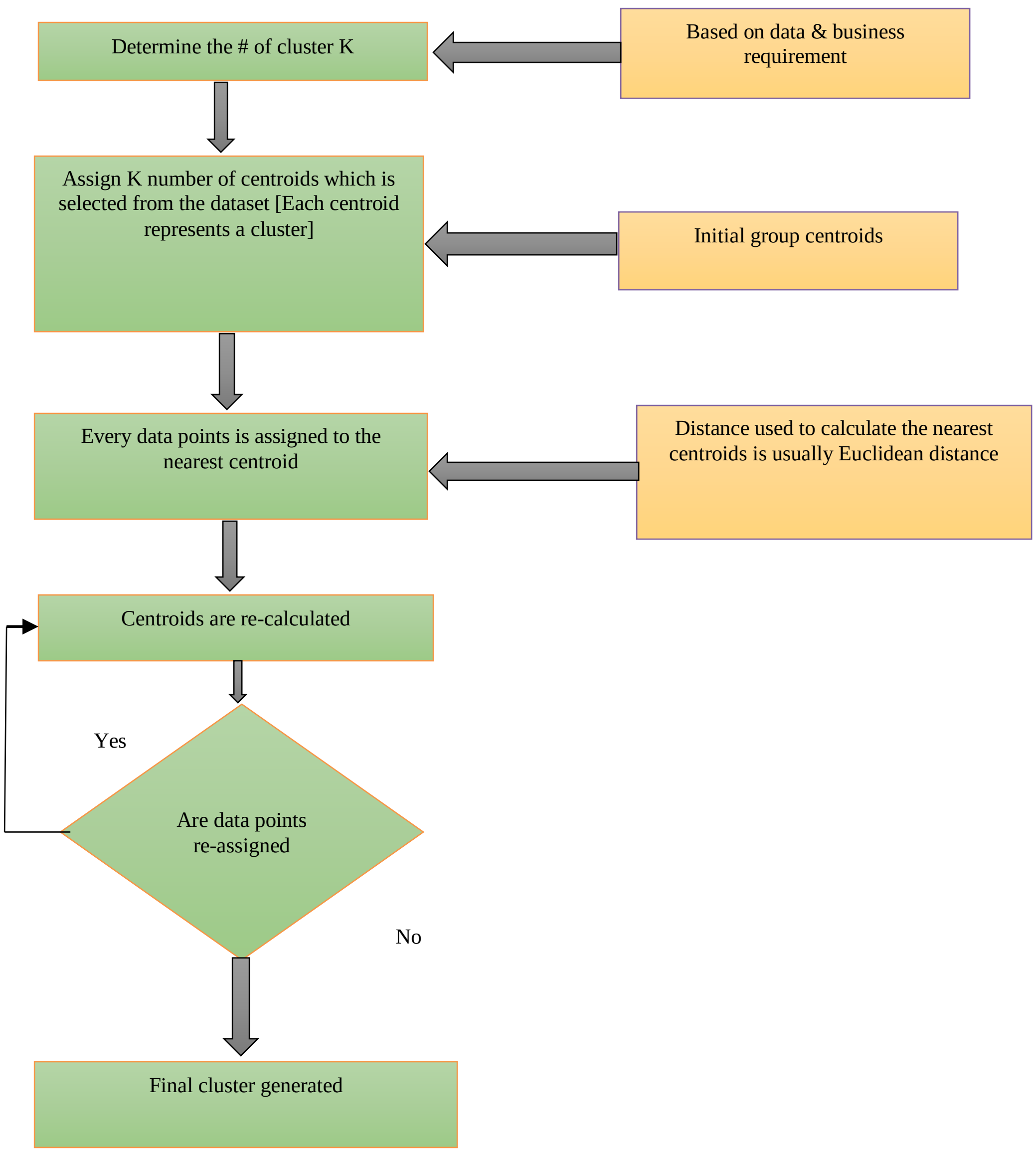

Figure 4: Flowchart of Region based Segmentation

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3.4 Feature Extraction

After segmentation, the GLCM highlights are separated from the Gray Level Co-Occurrence Matrix (GLCM) picture, which is the perceptible strategy for investigating the texture that takes about the pixel spatial connection.

The GLCM reason for existing is to characterize the picture texture by estimating the spatial connection between the pixels in the pictures. That matrix removes the factual measures. The number of counterbalances that speak to pixel associations of shifting bearing and separation should consistently be exhibited right now. Let P_{ij} is the $(i,j)^{th}$ N speaks to the number of explicit degrees of gray in the quantized picture.

The various features extracted are characterized as follows:

$$contrast = \sum_{i=0}^{N_P-1}\sum_{j=0}^{N_P-1}(i-j)^2 p(i,j) \quad (9)$$

$$correlation = \sum_{i=0}^{N_P-1}\sum_{j=0}^{N_P-1}\frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \quad (10)$$

$$Energy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}p^2(i,j) \quad (11)$$

$$Homogeneity = \sum_{i=0}^{N_P-1}\sum_{j=0}^{N_P-1}\frac{p(i,j)}{1+|i-j|} \quad (12)$$

$$Dissimilarity = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}p(i,j)|i-j| \quad (13)$$

$$Entropy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}p(i,j)\log(p(i,j)) \quad (14)$$

3.5 Image Classification

SVM's (Support Vector Machines) are a helpful arrangement methodology each training set is assigned with one target regard (for example class marks) and a couple of properties "(for example features or watched experimental factors), which can be use to stamp the test documentation with the be of help of training information. Here, the essential working of SVM is to make and group a limit between other contrastingly named information. The Support vector machine was at first intended for a binary arrangement. To stretch out SVM to the multi-class situation, various grouping models were proposed by Crammer and Singer.

Figure 5 shows the classification stage, that speak to multi-class and strong lines speak to the class limits. Run lines speak to the positive edges of the five stars.

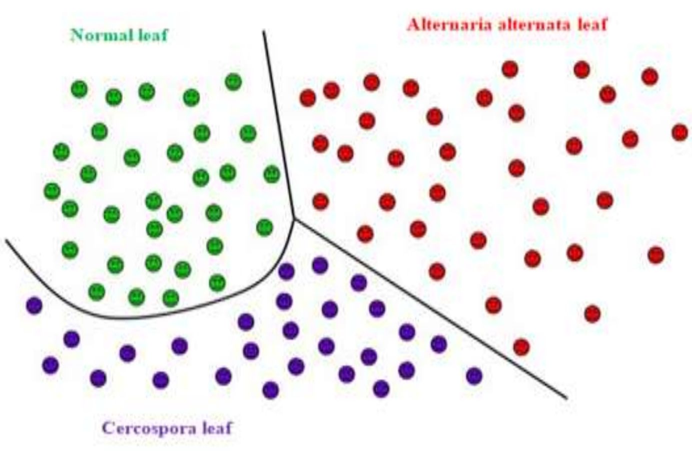

Figure 5: Multiclass SVM

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The Loss function is attributed in this procedure. The training set is provided by the,

$$\xi_{m,n} = 1 - f_{ym}(x_m) + f_i(x_m) \quad (15)$$

Loss function added up all defects of the positive function margin and is provided by,

$$\xi_m^{(1)} = \sum_{i \neq ym} [\epsilon_{m,n}] \quad (16)$$

$$\xi_{m,n} = 2 - f_{ym}(x_m) + f_i(x_m) \quad (17)$$

Convoluted multi-class SVM by adding a relaxed classification error limit reduces the size of the resulting dual problem from $l * k * l$.

The integrated link formed between various research studies like approximation and regularization of functions, noise interjection and pattern recognition are the significant attributes of RBFNN. The quick learning ability of RBFNN algorithm with its simple topology and locally tuned neurons partly increases their popularity.

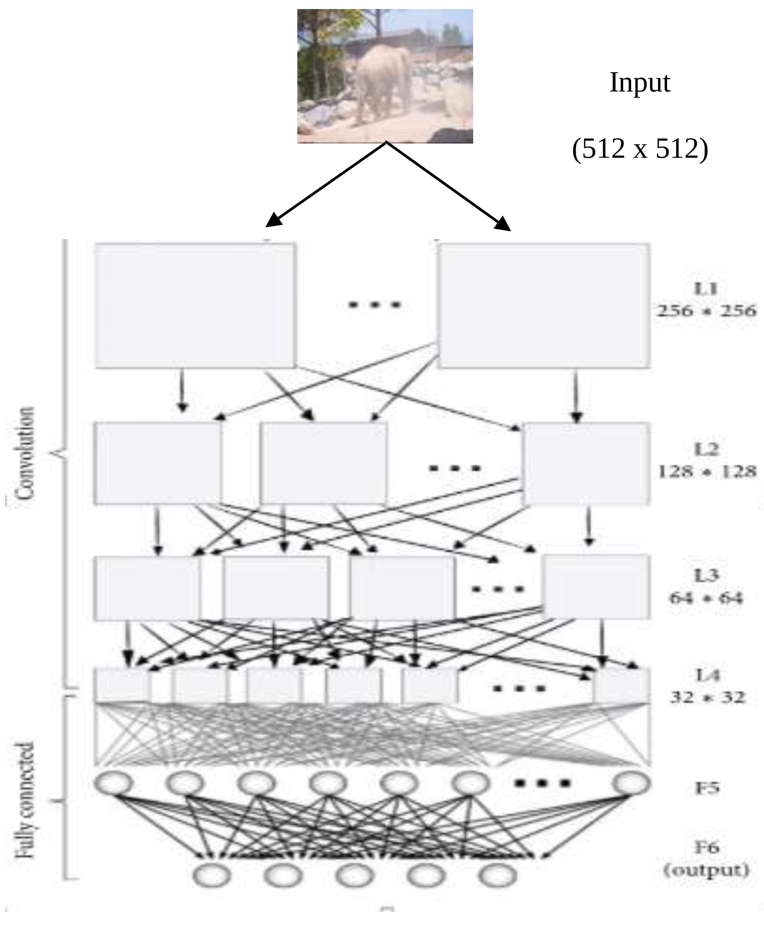

Figure 6: Classification Algorithm Flow Diagram

3.6 Security

The Protection of the pictures is significant in the present picture correspondence framework. Protecting picture information from unapproved clients is significant. It's a moving assignment to identify and discover unapproved clients. Different analysts have proposed various methods for verifying the transmission of pictures.

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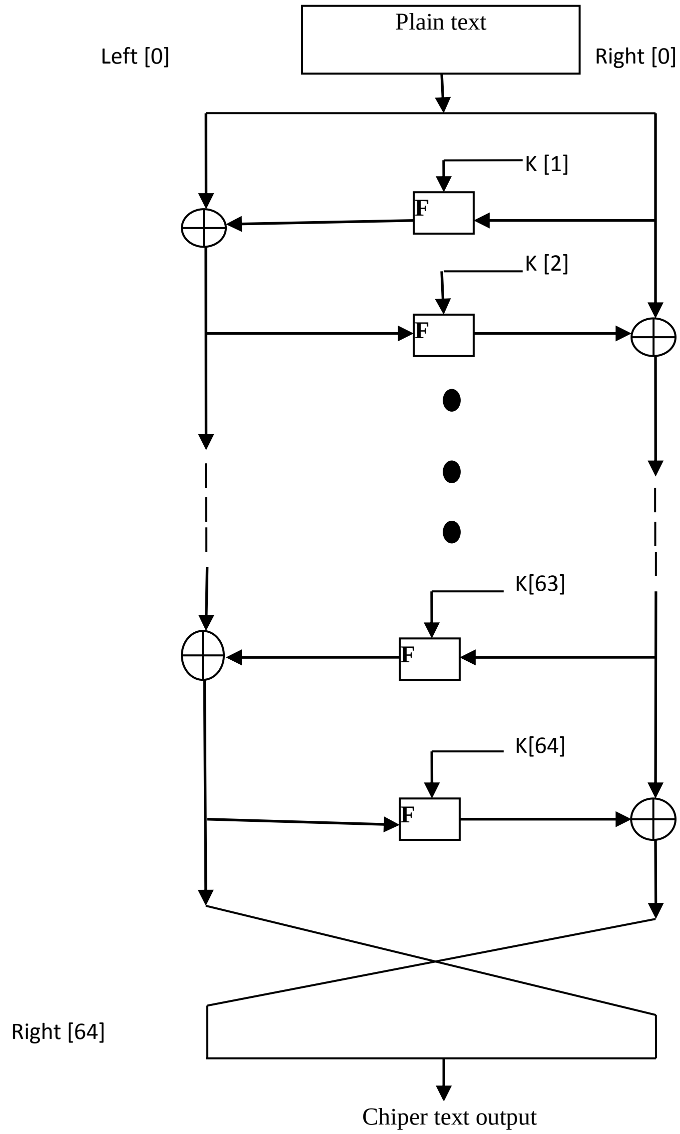

Figure 7

3.6.1 Encryption

Tiny Encryption Algorithm (TEA) is an extraordinarily quick, direct and Feistel-based block cipher that was created cryptographic calculations correlations with a few different calculations, for example, IDEA and AES.TEA. TEA is intended to take out memory impression and advance speed by debilitating and making straightforward tasks simple while accomplishing high safety by performing such basic activities a few times.

IV. RESULT AND DISCUSSION

To evaluate the performance of the proposed algorithm, we conduct extensive experiments using a video image database for different types of diseases, and compare with four feature extraction based crop video recognition methods: Support Vector Machines (SVM) *(Rumpf et al., 2010)*, K-means-based segmentation followed by neural-

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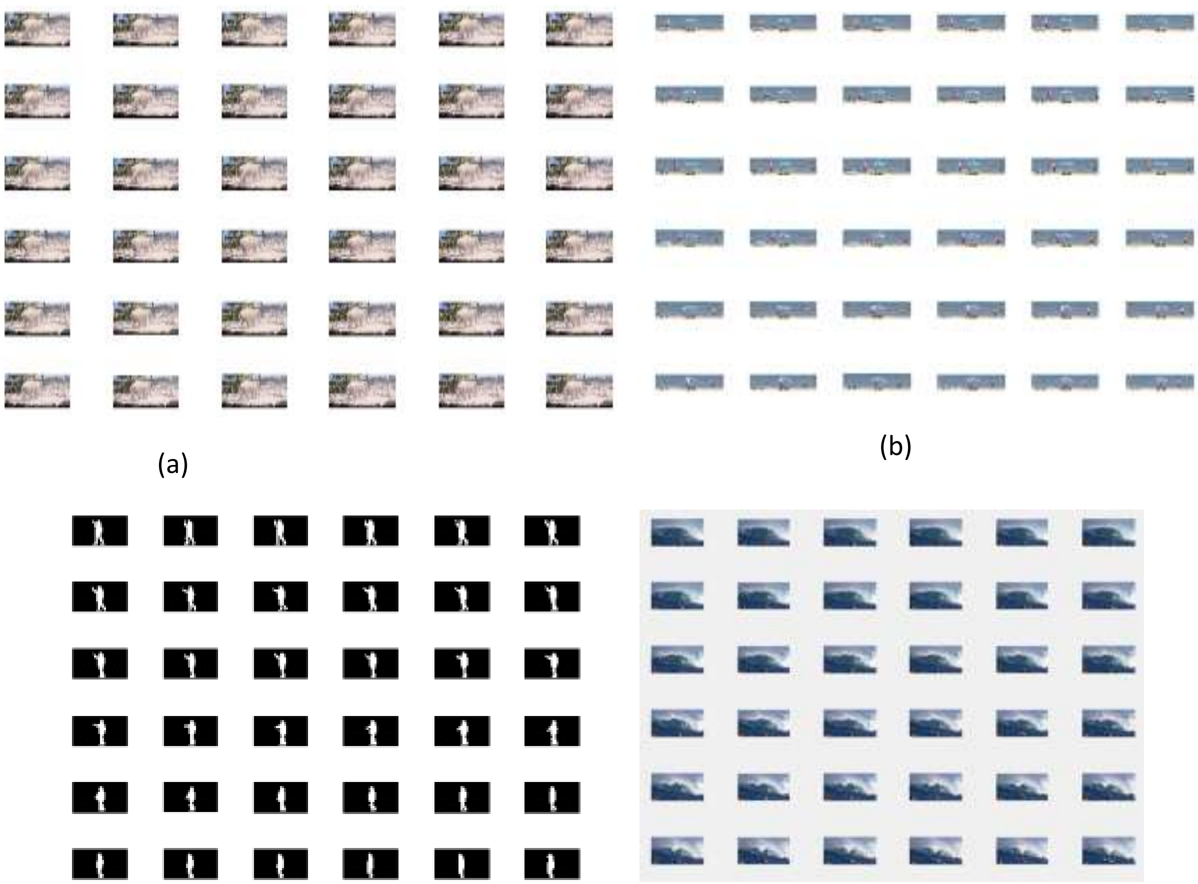
network-based classification (KMSNN) *(Al-Bashish et al., 2011)*, texture feature (TF) based classification *(Arivazhagan et al., 2013)*, and plant video image (PLI) based classification *(Zhang et al., 2015)*. All the experiments are carried out on a 1.8 GHz computer with 2 GB RAM. MATLAB software packages are to solve the l1-minimization problem in SR and perform lesion segmentation described in Sections 2 and 4. The Video input pictures are gotten from the Arkansas database.

(a) (b) (c)

Figure 8: Sample Video File



(a) (b) (c) (d)

Figure 9: Feature Extracted Video Frame Sample Images

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The purpose of data about assignments in k clusters is mutually exclusive and returns the clustered index to which each observation was assigned. The clustering continues to operate on current observations and permits a single performance rating throughout the clustering. Clustering offers several ways of clustering efficiency which can be seen in figure 10, including cluster 1, cluster 2 and cluster 3, and features shown in table 1.From the segmented image the features like contrast, Energy, Homogeneity, Dissimilarity, Entropy.

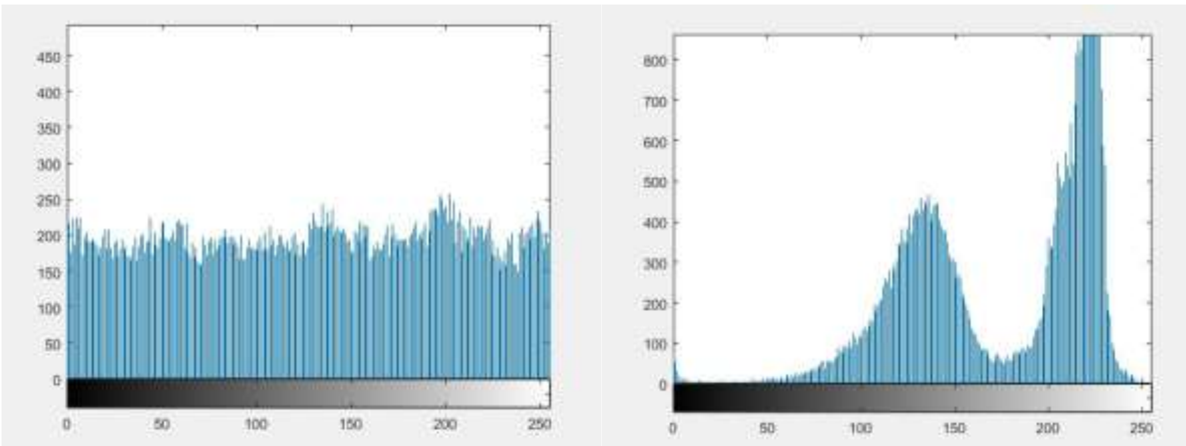

Figure 10: Histogram Equalization Plot

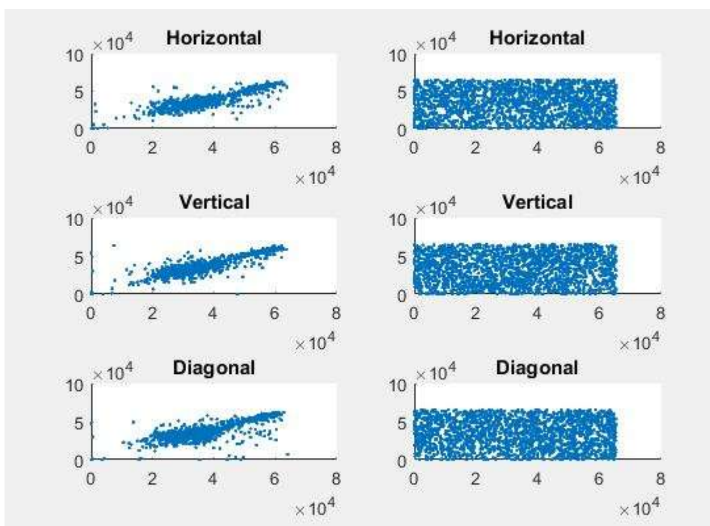

Figure 11: Horizontal, Vertical and Diagonal Plot for Clustering Image

Table 1: GLCM Features

Features	Contrast	Correlation	Energy	Homogeneity	Dissimilarity	Entropy
1	9.3200	0.6853	0.3627	0.7919	0.1472	1.6464
2	9.7558	0.6550	0.3551	0.8255	0.8764	1.4452
3	10.0830	0.0676	0.4065	0.8057	0.0198	1.5847
4	10.8067	0.5615	0.3551	0.7988	0.1101	1.3322
5	9.2068	0.5330	0.4150	0.8000	0.0042	1.5315

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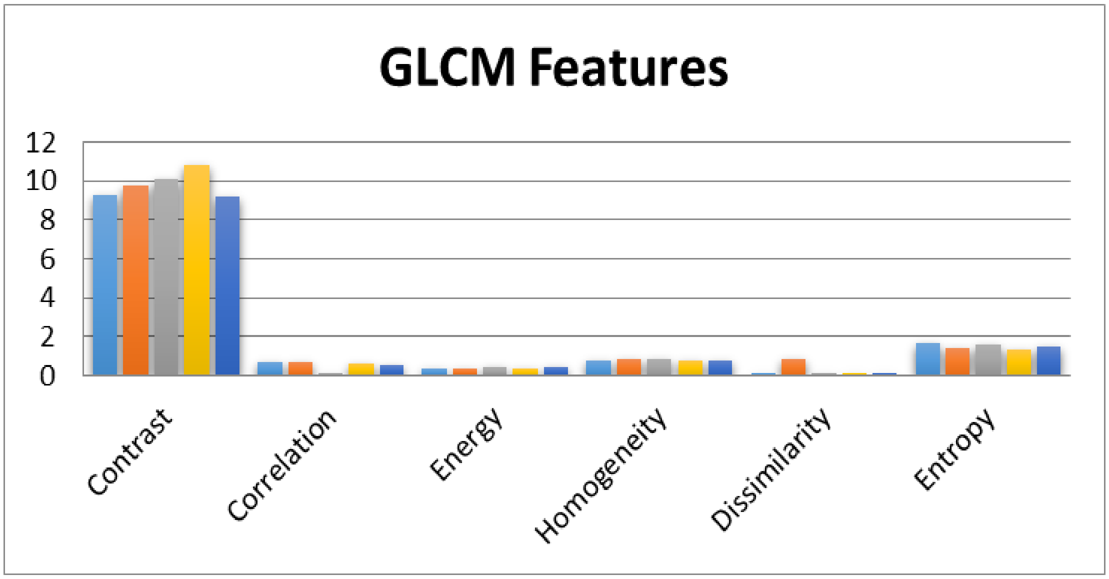

Figure 12: Graphical Representation for GLCM Features

The statistical characteristics are estimated and shown in Table 1, and the simple geometric function representation is shown in Figure 15. Uncertainty matrix classifier multiclass SVM is 97.2 %. Multiclass SVM seems to have a high precision compared to a single PSO-SVM classifier. Matrix number represents those establishments in a predicted class whereas each column represents establishments in an actual class.

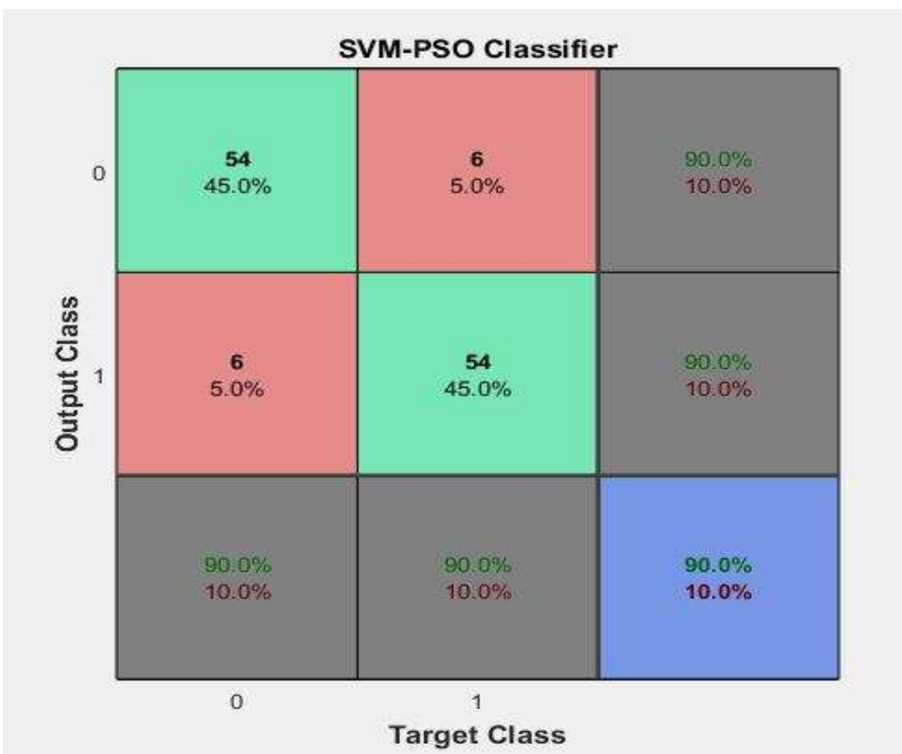

Figure 13: Result of Existing Method

DOI: 10.37200/IJPR/V24I5/PR2020139
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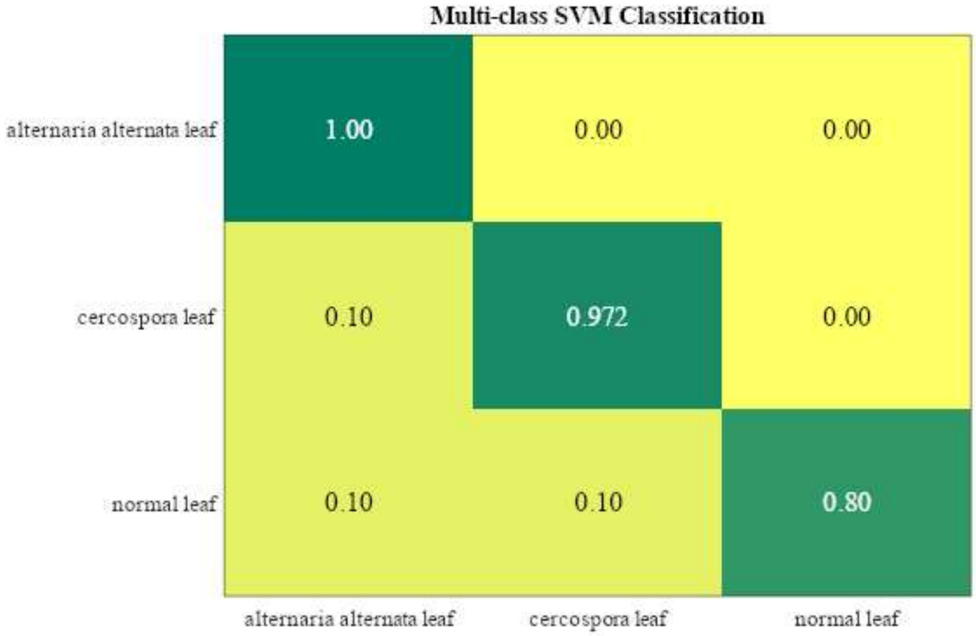

Figure 14: Confusion Matrix of Multi-Class SVM

According to the rate values, the precision level increases with both the image quality enhancement.

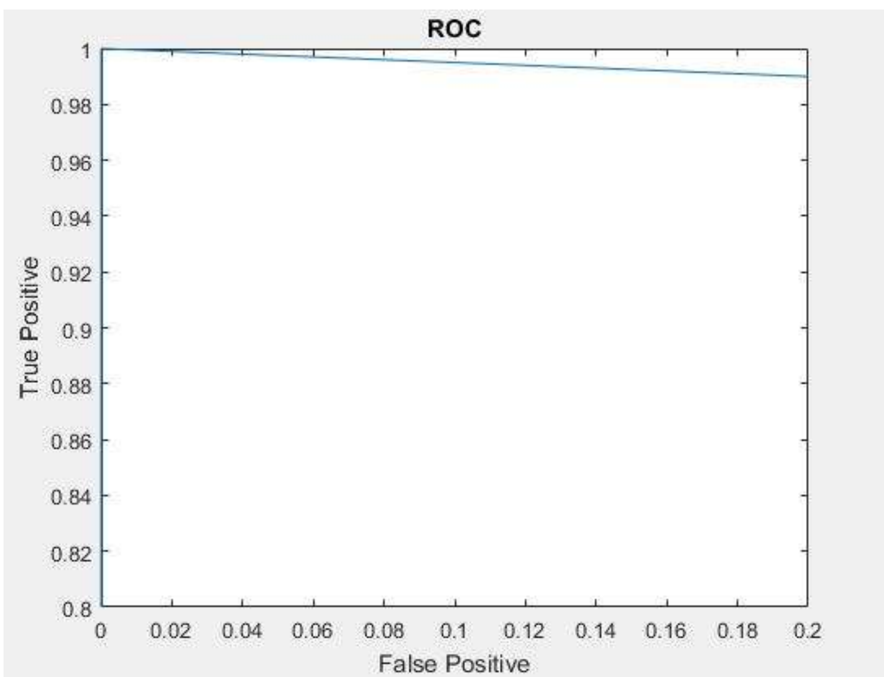

Figure 15: ROC Curve Plot

Results of those SVM Classifier accurately categorized video images are included in figure: 14.

Comparison was made of the accuracy of the specific classifier, defined in table 2 and shown in figure 16.

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Table 2: Classifier Performance

Classifier	**KNN**	**ANN**	**Multi Class SVM**
Accuracy	94.8 %	96.3 %	97.2 %
Error	5.2 %	3.7 %	2.8 %

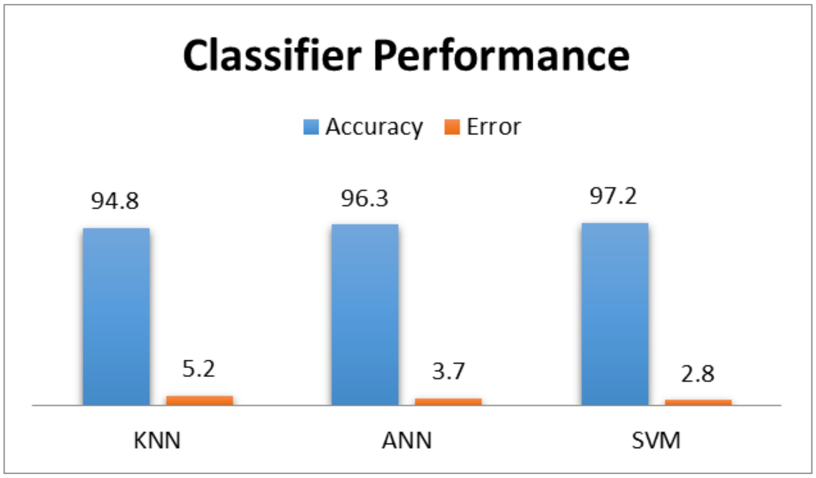

Figure 16: Accuracy and Error Plot

The proposed approach is compared to previous methods. For KNN classifier, the error rate is 5.2% for ANN classifier, the error rate is 3.7 %. As compared to KNN and ANN Multiclass SVM has low error, the high precision rate is 97.2 %.

Encryption is the method of encoding a message or data such that it can only be accessed by authorized parties, and those not authorized cannot. The unapproved individuals cannot. The classifier's output is encoded using the TEA algorithm and the encrypted data shown in figure 16.

V. Conclusion

Through these strategies, video frame can be detected, and the video management techniques could be used to overcome problems while reducing humans and environmental levels of risk. The feature extraction methodology helps isolate the infected video and also recognize the video frame image that used the SVM classifier in multiclass. This proposed approach will significantly help to identify video frame image with an accuracy of 97.2% where the error rate is 2.8% and minimal numerical effort compared with other computational models. The time consuming is lower compared with previous methods. More future prospects can be created by creating a better segmentation approach; identifying better feature extraction and classification algorithms, and NN (Neural Network's) to enhance the ultimate awareness of the classification process.

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