ABUAD Journal of Engineering Research and Development (AJERD)
ISSN (online): 2645-2685; ISSN (print): 2756-6811

Volume 7, Issue 1, 169-177

Performance Evaluation of Some Selected Classification Algorithms in a Facial Recognition System

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Date Submitted: 27/02/2024
Date Accepted: 26/04/2027
Date Published: 16/05/2024

***Abstract**: Facial Recognition (FR) has been an active area of research and has diverse applicable environment, it continues to be a challenging research topic. With the development of image processing and pattern recognition technology, there are many challenges in machine learning to select the appropriate classification algorithms, most especially in the area of classification of extracted features to have low classification time, high sensitivity and accuracy of the classification algorithms, so it is very important to explore the performance of different algorithms in image classification. The three selected supervised learning classification algorithms: Learning Vector Quantization (LVQ), Relevance Vector Machine (RVM), and Support Vector Machine (SVM) performance were evaluated so as to know the most effective out of the selected algorithms for facial images classification. The development of the system has four stages, the first stage is image acquisition and 180 images were taken by digital camera under same illumination and light colour background. The second stage is pre-processing to improve the images data by suppressing unwilling distortion; grayscale and normalization were used for image pre-processing. The third stage is feature extraction; Discrete Cosine Transform (DCT) is adopted for this purpose. While the fourth stage is face recognition classification, Receiver Operating Characteristics (ROC) was used to test the performance of each the three algorithms. However the Learning Vector Quantization algorithm, Relevance Vector Machine and Support Vector Machine performance have not been compared together to the most effective out of the three algorithms in term of False Positive Rate, Sensitivity, Specificity, Precision, Accuracy and Computation Time. Hence, this work evaluated the performance of the Learning Vector Quantization; Relevance Vector Machine and Support Vector Machine classification algorithms in facial recognition system and Support Vector Machine outwit the other two algorithms in facial recognition in term of specificity, recognition time and recognition accuracy at different threshold.*

***Keywords**: Support Vector Machine, Relevance Vector Machine, Learning Vector Quantization, False Positive Rate, Facial Recognition.*

1. INTRODUCTION

Safety is a top priority in human lives; human face recognition has been extensively studied over the past 20 years. It has numerous useful applications, including access control, security monitoring, and surveillance systems. Researchers in the fields of computer vision, psychology, neuroscience, security, and image processing are all interested in facial recognition. This biometric technology identifies individuals based on "who they are" rather than "what they have" or "what they know" [14]. Facial recognition is a biometric technology that recognizes faces based on a picture or set of photos captured by a camera or taken through photography [1]. Although there are certain similarities across faces, there are also significant differences in terms of gender, age, skin tone, and colour, making fake imitation exceedingly challenging. Different image qualities, facial expressions, facial furniture, backgrounds, and lighting conditions further exacerbate this issue [13].

Not only is facial recognition a thoroughly studied field in image analysis, pattern recognition, and biometrics, but it has also grown to play a significant role in our daily lives since it was first used as one of the identification techniques for e-passports and numerous security systems [22]. The safest and most useful authentication method is biometrics since it is nearly hard to steal, borrow, or create a false identity for a person [12]. Therefore, there is need to develop a more secure facial recognition system for authentication, hence, the implementation of the work to evaluate the performance of three classification algorithms in order to know the better in term of Recognition accuracy and Recognition time.

Relevance Vector Machine (RVM) is based on sparse Bayesian theory it is a machine learning methodology. It is well suitable for handling the problems of regression and classification, and it is extensively used in image retrieval, pattern recognition, and other fields. With the rapid development of the study on RVM, some effective improvements have been presented for the problems of computational complexity and training efficiency [21]. Developed from statistical learning theory, support vector machines (SVMs) are widely used in fields including text recognition, handwriting, character, and digit recognition, and more recently, satellite image categorization [3]. Traditionally, it is a classifier with two classes. Given an input data set (features), it attempts to predict the corresponding class. It is therefore a binary linear classifier that is non-probabilistic. Using an input set of training instances from the two classes, SVM attempts to construct a model. The foundation of Learning Vector Quantization (LVQ) is a series of statistical pattern classification methods that seek to learn prototypes, or codebook vectors, that represent class regions. Hyper-planes between prototypes define the class regions, resulting in Voronoi partitions. Teuvo Kohonen first presented the LVQ1 algorithm in the late 1980s, and over time, he created a number of variations. Since its creation, a tiny yet engaged group has been studying LVQ algorithms [7]. Because LVQ classifiers are predicated on the idea of class representatives (prototypes) and class areas, typically in the input space, they are especially straightforward and easy to comprehend. SVM performed better than the other two algorithms for facial images classification.

Li et al. [9] suggested a technique for face recognition that extracts Gabor features from face images using a mutual covariance reduction operation and the Gabor wavelet. The dimensions of the processed feature images were reduced, and features were extracted using weighted mutual covariance matrix. Based on the classification outcomes, face recognition was finished using the closest neighbour classifier. This method's low recognition efficiency was a concern, and the recognition procedure was laborious and time-consuming. Lin and Zhang [10] suggested a greedy approximation algorithm-based face recognition technique. The fundamental tenet of this approach was that tag cost could be used to regulate the quantity of tags in an album, and the face picture of the album structure represented the compatibility between tags. The album's personal information was modelled based on the tag cost, and a greedy approximation approach was provided to tackle the NP problem throughout the modelling phase. The maximum membership degree approach was used to complete face recognition after SVM training yielded the model parameters. The image denoising was low after de-noising, and this method was unable to successfully remove numerous sounds from the face image.

Feifei et al. [2] suggested a method for recognizing faces that used PCA for feature extraction and dimensionality reduction, and Pulse Coupled Neural Networks (PCNN) to efficiently suppress noise and cluster the distinctive area of noisy faces. SVM is used for classification and recognition. A face biometric algorithm using pose-invariant face databases is created by Joardar et al. [4]; the patch-wise self-similarity metric was used to extract features from the image. Utilizing the Far Infrared (FIR) database, the method was evaluated. Histogram equalization and convolution neural network-based face recognition technology was first presented by Yue and Lu [19]. Using this method, the convolution neural network was constructed using a deep learning framework, and the face image was preprocessed using histogram equalization. The ORL (Our Database of Faces) database was used in the experiment to measure the recognition rate. To raise the rate of face recognition Zhang and Malik [20] created a Local Binary Pattern Histogram (LBPH) algorithm with expression variation, illumination diversification, and attitude deflection. Rather of taking into account the intermediate values, this technique looks at the sample values' grey median neighborhood. This algorithm is shown to have a higher recognition rate than the LBPH algorithm. Singh et al. [16] introduced a facial landmark-based face recognition system. The analysis of the recognition involved determining the distance and slope between each face landmark. Both statistical methods and classifiers were used in the analysis. This method works well for facial identification using a small number of feature data and facial expressions in various orientations.

Khadhraoui et al. [6] offered a score level fusion-based hybrid face recognition system that is multimodal in both 2D and 3D. During the fusing stage, as opposed to the traditional fusion guidelines by Joshi et al. [5], the fused score for the ultimate choice is produced by applying a novel fusion rule that is based on the relevance vector machine (RVM). Liu et al. [11] Introduced a novel relevance vector machine (RVM) based facial recognition method. First, a facial image is preprocessed using the wavelet transform to lessen the effect of expression changes. After that, the processed face image's important features are extracted using the principle component analysis (PCA) technique. Lastly, the classification model for RVM is used to identify. The support vector machine (SVM) method is not as effective as the random vector machine (RVM) approach, which yields less desirable results when it comes to resilience and recognition rates.

Yu et al. [18] suggested a better additive cosine interval loss function in order to enhance the original one. To achieve the goal of decreasing the distance between classes and increasing the distance between classes, a value between 0 and 1 is subtracted from the cosine value of the angle between the feature and the target weight and added to the cosine value of the angle between the feature and the non-target weight. The best value is determined through experiments. A convolutional neural network with singular value face and attention combined with a face recognition model was suggested by Li and Liu, [8]; Peng et al. [15] and Wang et al. [17]. The approach first represents facial features using a normalized singular value matrix. Then, it adds the attention module to the input features and feeds them into a deep convolutional neural network.

Finally, it enhances the network's robustness by fusing cross-channel and spatial data. Ultimately, the network's iterative training process completes the classification and recognition of face photos. Zhou et al. [22].

2. METHODOLOGY

The proposed system has four stages; as it is stated in the Figure 1 and each stage is explained as follows:

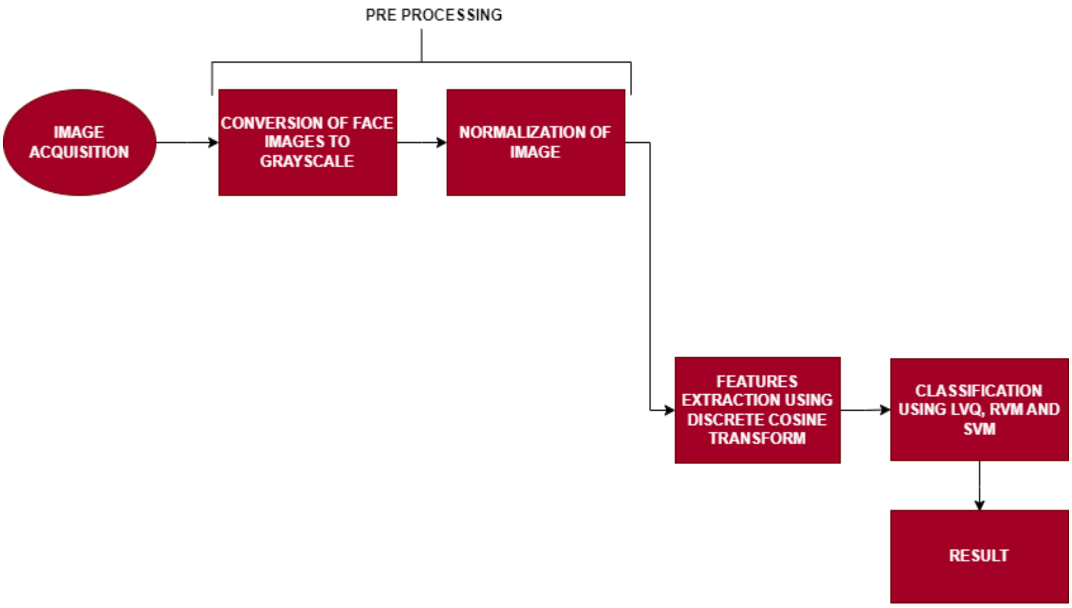


Figure 1: Proposed facial recognition system flow diagram

2.1 Acquisition of the Face Images

A faces of 40 subjects were captured with a digital camera in the size 100 x 100, 150 x 150, 200 x 200, 250 x 250 pixels with no alteration on the image. The images were taken under the same illumination and light color background, 6 images are captured for the 40 subjects and 180 images of which were used for training of the system while the remaining 60 images were used for testing the system.

2.2 Image Pre-processing

Pre-processing is the name used for operation of images at the lowest level of abstraction. The aim of preprocessing is to improve the images data by suppressing unwilling distortion and also enhancing some image feature important for further processing. The two image pre-processing method used in this research work was Grayscale and Normalization.

2.2.1 Conversion of face images to grayscale and vector

The images were captured with the digital camera are usually color images in 3- dimensional form 3D and it is converted to 2-dimensional image with pixel value ranging from 0 to 255. Because the human eye only contains three distinct colour receptors, each of which is sensitive to one of the three fundamental colors- red, green, and blue that is feasible to create nearly all visible colours by combining these colours. The human eye can detect about 350,000 colours to various combinations of receptor stimulation. A multi-spectral image with one band for each colour produces a weighted combination of the three primary colours for each pixel in an RGB colour image. An image that only contains grayscale (also known as gray level) colours is called a grayscale image. Usually, this is stored information about a matrix that can be transformed into a vector. The face vector aided normalization of the image in MATLAB. Figure 2 describe a neutral image converted to grayscale.

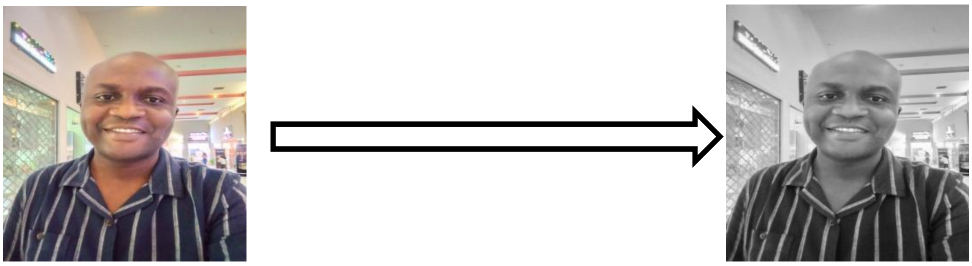


Figure 2: RGB to grayscale conversion of image

2.2.2 Face image normalization

Normalization removes feature that shares commonality in the face since the intensity of each face photograph may vary because they were taken at different times of the day or on separate days. The test images must be normalised to have an average intensity value in relation to the registered image in order to prevent these differences in light intensity. The sum of all pixel values divided by the total number of pixels yields the average intensity value for all registered images. By using histogram equalisation, it is ensured that the input pixel intensity, X, will be transformed to a new intensity value, x, by T. Parameter T is the transform function that results from multiplying a cumulative histogram by a scale factor, which is required to fit the new intensity value within the range of intensity values as in equation 1.

$$X = T(x) = \sum_{i=0}^{r} n_i \frac{\max intensity}{N} \tag{1}$$

2.3 Feature Extraction

Feature Extraction entails cutting down on the resources needed to explain a big data set. Discrete Cosine Transform (DCT) was used for feature extraction in this work. A finite series of data points can be expressed in terms of a sum of cosine functions pulsating at various frequencies using the Discrete Cosine Transform (DCT), an invertible linear transform. By using the direct DCT transform, the original is changed into the frequency domain. The transformed signal can then be returned to the original domain by using the inverse DCT transform. The DCT coefficients of the original signal indicate the significance of the frequencies it contains once it has been converted. Known as the DC-coefficient, the very first coefficient relates to the signal's lowest frequency and typically contains the majority of the pertinent (i.e., most representative) information from the original signal. The higher frequencies of the signal are mentioned by the final coefficient. These higher frequencies, which are most likely the result of noise, typically indicate more fine-grained or detailed signal information. Different information levels of the original signal are carried by the remaining coefficients, which are those between the first and last coefficients. Given that images are inherently two-dimensional, it is intriguing to apply a two-dimensional DCT (2D-DCT) in the field of image processing. The general equation for a 1D (N data items) DCT is defined as follows in Equation 2 and 3 respectively:

$$F(u) = \sqrt{\frac{2}{N}} \sum_{i=0}^{N-1} A(i) * \cos\left(\frac{u(2i+1)\pi}{2N}\right) * f(i)$$

$$F(u) = \sqrt{\frac{2}{N}} \sum_{i=0}^{N-1} A(i) * \cos\left(\frac{u(2i+1)\pi}{2N}\right) * f(i) \tag{2}$$

where

$$A(i) = \left\{\frac{1}{\sqrt{2}}\right\} \text{ for u=0}$$

Otherwise

f (i) is the input sequence.

The general equation for a 2D (N × M image) DCT is defined as follows:

$$F(u,v) = \sqrt{\frac{2}{N}} \sqrt{\frac{2}{M}} \sum_{i=0}^{N-1} A(i) * \cos\left(\frac{u(2i+1)\pi}{2N}\right) * \sum_{j=0}^{M-1} A(j) * \cos\left(\frac{v(2j+1)\pi}{2M}\right) * f(i,j) \tag{3}$$

Where,

$$A(i) = \left\{\frac{1}{\sqrt{2}}\right\} \text{ for u=0}$$

Otherwise

$$A(i) = \left\{\frac{1}{\sqrt{2}}\right\} \text{ for v=0}$$

Otherwise

f (i, j) is the 2D input sequence

2.4 Face Recognition Classifier

Learning Vector Quantization, Relevance Vector Machine and Support Vector Machine classifiers are used after feature extraction. These involve learning and classifying either as supervised or unsupervised. The performance of the three classifiers were tested by using Receiver Operating Characteristics (ROC) which was used to check the quality of the classifier from each class of classifier; ROC applies threshold values across the interval of 0 or 1.

3. RESULTS AND DISCUSSION

3.1 Experimental Setup

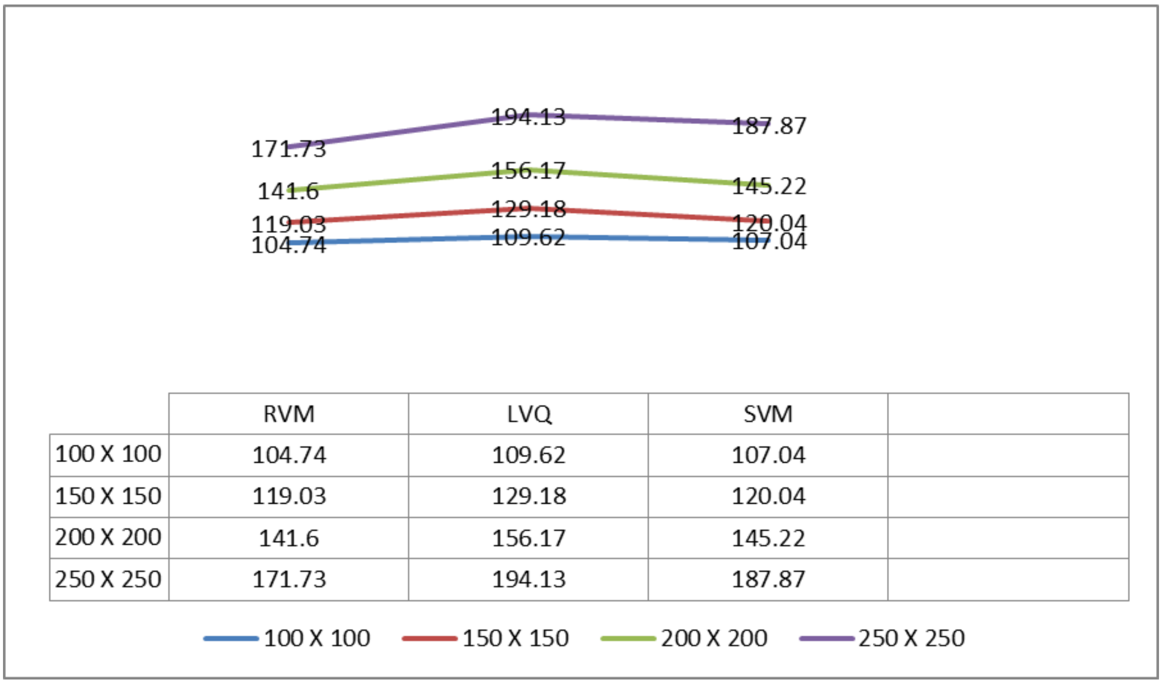
In order to determine the performance of the face recognition system using LVQ, RVM, SVM; an interactive Graphic User Interface (G.U.I) was developed with a real time database consisting of 40 subjects of face images. The development tools used was MATLAB 2014s version on window 7 ultimate 32 bits operating system Intel Core i5 CPU B960 @ 2.20GHZ 4GB random access memory and 500GB hard disk drive. The system was experimented with 180 images out of which 120 images were used in training the dataset meaning 3 images per 40 subjects and 60 images were used in testing the face recognition system, The system was experimented using different threshold value 0.20, 0.30, 0.40, 0.50, 0.60 and the comparative result of the three algorithms on face dataset were generated and reported in Table.4.5 based on recognition accuracy, computational time, false positive rate, sensitivity, precision and specificity. The decision taken to classify the images as true positive, false positive, false negative and true negative was determined by the threshold value. The threshold value was taken as some factor of maximum value of minimum Euclidean distances of each image from other images. Threshold is the acceptance or the rejection of a facial template match which is dependent on the match score falling above or below the threshold. The threshold value is adjustable within the facial recognition system.

3.2 Experimental Dataset

The dataset used contain 180 images out of which 120 images for training the model while 60 images are used to test the model. The training is carried out using LVQ, RVM and SVM as shown in Table 1 the training time generated by LVQ is higher than RVM and SVM as the dimension size increases from 100 x 100 to 250 x 250 pixels

3.3 Trained Result

120 images were used in training the dataset meaning 3 images per 40 subjects, in generating the training time, the time spent increases as the dimensional size increases which implies the more the features in the training set, the more the computational time. The training time generated by application of LVQ with 100 x 100 pixel dimension resolution was 109.62 seconds, 150 x150 was 129.17 seconds 200 x 200 pixel resolutions was 156.17 seconds, 250 x 250 pixel was 194.13seconds The training time generated by application of RVM with 100 x100 pixel dimension resolution was 104.74seconds, 150 x 150 pixel dimension resolution was 119.03 seconds 200 x 200 pixel dimension resolution was 141.60 seconds, 250 x 250 pixel dimension resolutions was 187.87 seconds while the training time generated by SVM with 100 x 100 pixel dimension resolution was 107.58seconds, 150 x 150 was 1.04 seconds 200 x 200 pixel resolutions was 145.22 seconds, 250 x 250 pixel was 187.87 seconds as presented in Figure 3.



	RVM	LVQ	SVM	
100 X 100	104.74	109.62	107.04	
150 X 150	119.03	129.18	120.04	
200 X 200	141.6	156.17	145.22	
250 X 250	171.73	194.13	187.87	

Figure 3: The training time generated by the three algorithms

3.4 Results of learning Vector Quantization (LVQ)

Table 1 presented performance evaluation based on recognition accuracy, computation time, precision, False Positive Rate, sensitivity (i.e. True positive Rate), and specificity (i.e. True Negative Rate) as analyzed with respect to learning vector quantization. The accuracy generated by LVQ is analyzed by using different threshold values. The results of the experiment with LVQ are shown in Table 1 and Figure 4 respectively. It was noticed that recognition accuracy with LVQ at 100 x 100 pixel with varied threshold value as the threshold values was increase the recognition accuracy also increase that is at threshold value 0.20 the recognition accuracy was 66.67% 0.30 the accuracy was 6.67% at 0.40 the accuracy was 75% at 0.50 the recognition accuracy was 83.30% and 0.60 the recognition accuracy was 83.30% Likewise, the sensitivity, specificity and precision which also increase with the threshold value. On a Contrary the false positive rate decreases with the increasing threshold value that is at threshold value 0.20 the False positive rate was 45.15% at 0.30 threshold value the FPR was 42.87 also at 0.40 the FPR was 25.00% and 0.50 and 0.60 the FPR remain the same at 12.50%.

Table 1: Results of LVQ

Thresh	Dimension	TP	FP	FN	TN	FPR	Sens	Spec	Prec	Acc	Comp time (s)
0.20	100 x 100	17	15	5	23	46.15	77.77	60.00	53.85	66.66	104.05
0.30	100 x 100	20	15	5	20	42.86	80.00	57.14	57.14	66.66	108.23
0.40	100 x 100	30	10	5	15	25.00	85.71	60.00	75.00	75.00	108.39
0.50	100 x 100	35	5	5	15	12.50	87.50	75.00	87.50	83.30	104.13
0.60	100 x 100	35	5	5	15	12.50	87.50	75.00	87.50	83.30	104.10

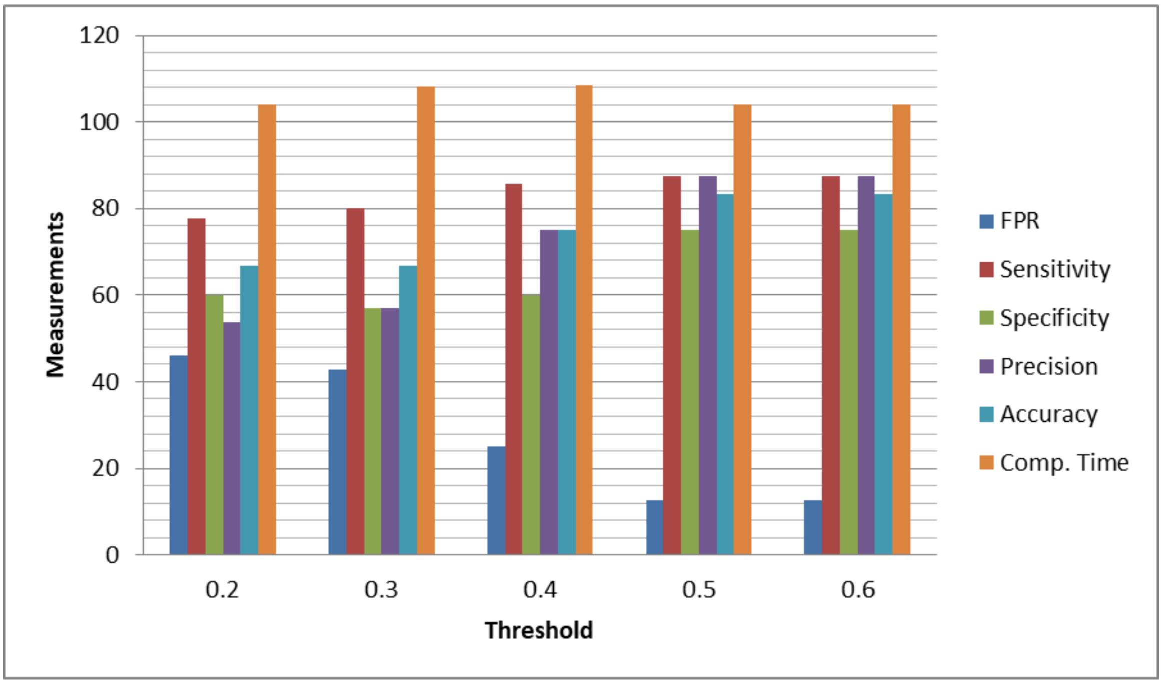


Figure 4: The result of Learning Vector Quantization at various thresholds

3.5 Result of SVM

Similar procedure was carried out with LVQ in terms of its FPR, sensitivity, Specificity, Recognition accuracy, precision and Computation time at the same resolution of 100 x 100 pixel resolution at a varied threshold value of 0.20, 0.30, 0.40, 0.50,and 0.60 each as shown in Table 2 and Figure 5 respectively. It was noticed that recognition accuracy with SVM at 100 x 100 pixel resolution with threshold value 0.20 the recognition accuracy was 80.00%, at 0.30 the recognition accuracy was 84.29%, at 0.40 the recognition accuracy was 87.14%, at 0.50 threshold value the recognition accuracy 88.57% and at 0.60 thresholds value the recognition accuracy was 88.57%. Likewise the sensitivity, precision also increase with increasing threshold value. Specificity at 0.20 threshold value was 58.82%, 0.30 threshold value 63.64% at 0.40 was 66.67% at 0.50 the specificity was 62.50 and at 0.60 it was 40.00%. On a contrary, the FPR decreases and the threshold value was increase from 0.20 threshold value to 0.60 that is at 0.20 threshold value the FPR was 13.20%, 0.30%, at 0.30 it was 7.14% at 0.40 the FPR was 5.17%

Table 2: Results of Support Vector Machine

Thresh	Dimension	TP	FP	FN	TN	FPR	Sens	Spec	Prec	Acc	Comptime(s)
0.20	100 x 100	36	7	7	10	13.21	86.79	58.82	86.79	80.00	90.93
0.30	100 x 100	42	4	7	7	7.14	88.13	63.64	92.86	84.29	90.59
0.40	100 x 100	45	3	6	6	5.17	90.16	66.67	94.83	87.14	89.93
0.50	100 x 100	47	3	5	5	5.00	91.94	62.50	95.00	88.57	90.48
0.60	100 x 100	50	3	5	2	4.76	92.31	40.00	95.24	88.57	89.36

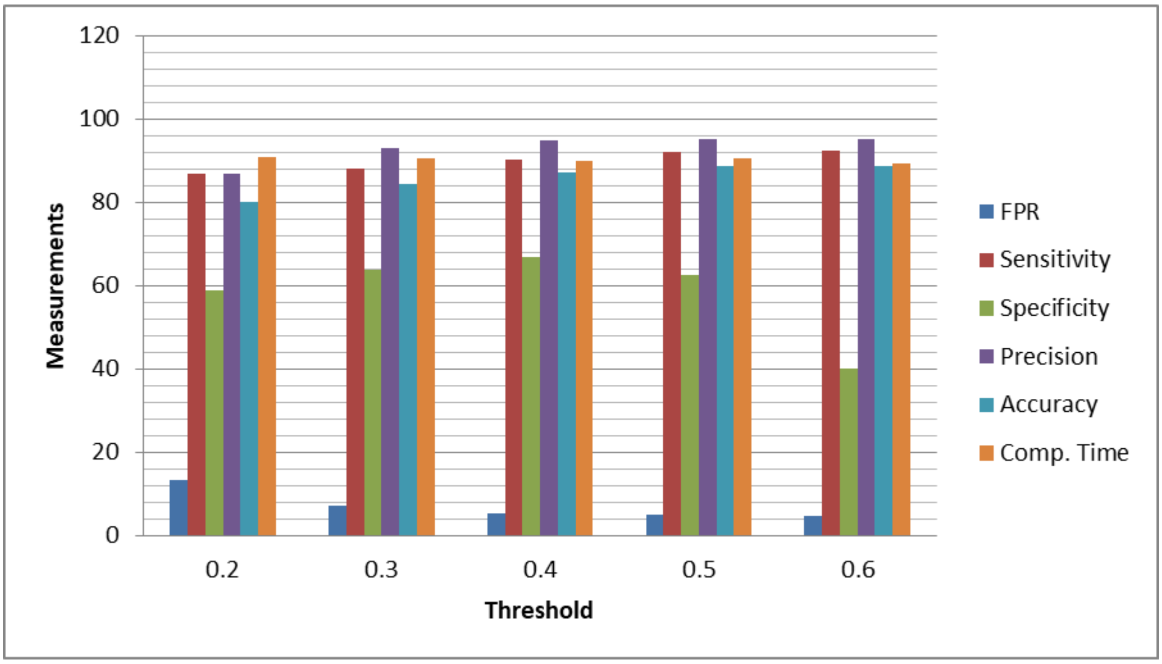


Figure 5: The result of Support Vector Machine at various thresholds

3.6 Result for RVM

Table 3 presented performance evaluation based on recognition accuracy, computation time, False Positive Rate, sensitivity, specificity as analyzed with respect to RVM at the same resolution of 100 x 100 pixel resolution at a varied threshold value of 0.20, 0.30, 0.40, 0.50,and 0.60 each as shown in Table 3 and Figure 6 respectively. It was noticed that recognition accuracy with RVM at 100 x 100 pixel resolution with threshold value varied that is at threshold value 0.20 the recognition accuracy was 71.43% 0.30 threshold value the accuracy was 71.43% and at 0.40 the accuracy was 74.29%, at 0.50 the accuracy was 77.14% and at 0.60 the accuracy was 77.14% likewise the sensitivity, precision also increase as threshold value was increased. However, the FPR decreases as the threshold value increases, at threshold value 0.20 the FPR was 26.09% at 0.30 the FPR was 25.53% at 0.40 the FPR was 22.45% and at 0.50 and 0.60 threshold value the FPR was 21.57%.

Table 3: Results of Relevance Vector Machine (RVM)

Thresh	Dimension	TP	FP	FN	TN	FPR	Sens.	Spec.	Prec.	Acc.	Comp time(s)
0.20	100 x 100	34	12	8	16	26.09	80.95	57.14	73.91	71.43	91.48
0.30	100 x 100	25	12	8	15	25.53	81.40	55.56	74.47	71.43	92.24
0.40	100 x 100	28	11	7	14	22.45	84.44	56.00	77.55	74.29	91.68
0.50	100 x 100	30	11	5	14	21.57	88.88	56.00	78.43	77.14	91.74
0.60	100 x 100	30	11	5	14	21.57	88.88	56.00	78.43	77.14	91.74

3.7 Comparison Results between LVQ, RVM and SVM

Summarily, Table 4 shows the measured parameters and value obtained after implementing the three considered algorithms on face images. The classified results are interpreted as follows. The recognition accuracy, computation time, sensitivity, false positive rate and specificity of the RVM, SVM, and LVQ are compared and determined at different threshold values of 0.20, 0.30, 0.40, 0.50, and 0.60 at the pixel resolution of 100 x 100. The comparison result shows that at threshold value 0.20, LVQ has 66.67 percent accuracy at 104.05sec, RVM has 71.43 percent accuracy at 91.48secs while SVM has 80 percent accuracy at 90.93sec While the threshold value was increased to 0.30, the LVQ has a recognition accuracy of 66.67 percent at 108.23 sec and RVM has an accuracy of 71.43 percent at 91.68sec and SVM has an accuracy of 84.29 percent at 90.59 sec.

At threshold value 0.40, LVQ has 75 percent accuracy and the computation time was 108.39 sec ,RVM has accuracy of 74.29 percent at 91.68 sec while SVM has 87.14 percent at 89.93 sec .At a threshold value of 0.50 ,LVQ has a recognition accuracy of 83.30 percent at 104.13 sec ,RVM has an accuracy of 77.14 percent at 91.74 sec and SVM has 88.57 percent at 90.48 sec .At a threshold value 0.60 , LVQ has an accuracy of 83.30 percent at 104.13sec RVM has a recognition accuracy of 77.14 percent at 91.74sec and SVM has a recognition accuracy of 88.57 percent at 89.36 sec.

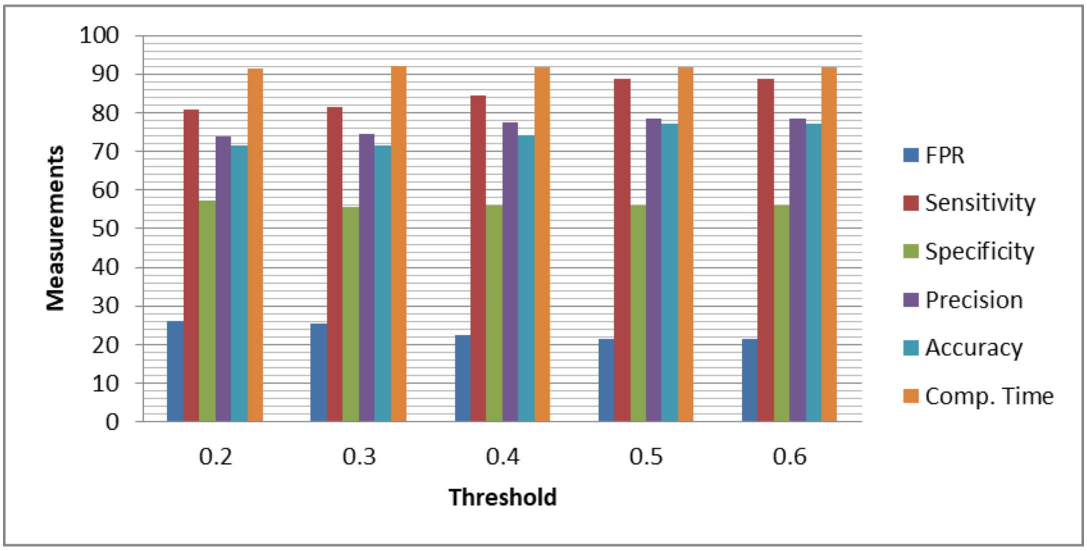


Figure 6: The result of Relevance Vector Machine at various thresholds

Table 4: Table showing combined results of RVM, LVQ and SVM at varied threshold

Threshold	Algorithm	FPR	Sens.	Spec.	Prec.	Acc.	Comp Time(s)
0.20	LVQ	46.15	77.77	60.00	53.84	66.66	104.05
	RVM	26.09	80.95	57.14	73.91	71.43	91.48
	SVM	13.21	86.79	58.82	86.79	80.00	90.93
0.30	LVQ	42.86	80.00	57.14	57.14	66.66	108.23
	RVM	25.53	81.40	55.56	74.47	71.43	92.24
	SVM	7.14	88.13	63.64	92.86	84.29	90.59
0.40	LVQ	25.00	85.71	60.00	75.00	75.00	108.39
	RVM	22.45	84.44	56.00	77.55	74.29	91.68
	SVM	5.17	90.16	66.67	94.83	87.14	89.93
0.50	LVQ	12.50	87.50	75.00	87.50	83.30	104.13
	RVM	21.57	88.88	56.00	78.43	77.14	91.74
	SVM	5.00	91.94	62.50	95.00	88.57	90.48
0.60	LVQ	12.50	87.50	75.00	87.50	83.30	104.13
	RVM	21.57	88.88	56.00	78.43	77.14	91.74
	SVM	4.76	92.31	40.00	95.24	88.57	89.36

4. CONCLUSION AND RECOMMENDATION

This paper compares and introduces the intrinsic feature of RVM, SVM and LVQ algorithms on face recognition system in other to determine the most effective while compared. The study familiarized the system with a real-time database which in turn was pre-processed and then underwent feature extraction processes via Discrete Cosine Transform for easy classification. The 180 images used were able to expose and put to examination the inherent abilities and capabilities of three algorithms examined, it was deducted that the recognition accuracy and sensitivity at different threshold generated higher values with SVM than the other two LVQ and RVM. The performance of the algorithms at each stage of the process contributed to the better classification of the face image hence the essence of the study was actualized as a result of the performance of SVM outwits the other two algorithms at different threshold. Future work can be carried out by comparing other algorithms with the considered algorithm in this research to determine the most effective and well performed algorithm in terms of recognition time, precision, accuracy and computation time.

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