4

Enhanced Biometric Iris Authentication in Low Powered Resource Constrained Mobile Devices using the Proposed PCA-SVMED Method

4.1 Introduction

The main objective of this chapter is to develop a comprehensive approach for mobile device and data security based on iris biometric authentication. Mobile devices are ubiquitous. Consequently, more confidential data is now stored on these devices which increases the risk of information and identity theft. It is essential to provide a reliable method for securing these devices and their data against unauthorized access. Widely used knowledge-based authentication mechanisms like PINs and passwords are not well suited for mobile devices as the capabilities of user interfaces are very limited. The objective is to create a reliable, portable way of identifying and authenticating the mobile device users.

The era of using biometric authentication for mobile devices is imminent. Biometrics employs physiological or behavioral characteristics to accurately identify an object. Among all biometric traits such as fingerprint, face, palm print, gait, voice, iris, dental radiographs etc. Iris recognition is the most consistent and accurate one. A major advantage is that no additional hardware component is needed as a camera is integrated in a mobile device. The effort is not only to develop new innovative algorithms to improve performance in iris recognition, but also to develop awareness on the usability of this method by focusing on activity recognition and continuous authentication, as well as assuring security against deliberate attackers. The proposed contribution one describes an approach to adapt iris recognition for resource-constrained mobile phones by reducing its computational complexity.

In this chapter, the combined algorithm namely, Principal Component Analysis with the Support Vector Machine and Euclidian Distance (PCA-SVMED) is used to recognize and authenticate the user of the mobile device. The biometric system can identify users based on physiological or behavioral characteristics. Iris recognition in mobile devices is used to authenticate the users of mobile device, by detecting the unauthorized access to mobile device by matching dataset. The template matching is the process where the features are considered to match with iris images for mobile device authentication. Initially, the iris image is captured using an Android application and the images are pre-processed. The size of iris database image is dimensionally reduced using the Principal Component Analysis (PCA). The PCA effectively reduces the number of features and displays the data set in a low dimensional subspace. It minimizes the processing time and improves the accuracy in authentication process.

The authentication via identification (one-to-many template matching) or verification (one-to-one template matching) is based on Support Vector Machine (SVM) classification and Euclidean distance. The Euclidean distance is to measure the minimum distance between the feature and SVM structure. The methods used are explained below.

4.2 Steps of Proposed Contribution One - PCA-SVMED Method

The objective of the contribution one is to authenticate the of mobile device users using iris biometric based on their features and structures with better accuracy. The proposed contribution one consists of three steps and they are discussed below Figure 4.1 shows the three different steps of proposed contribution one namely,

- Acquisition and Pre-processing
- Feature Extraction and Reduction
- Detection and Classification

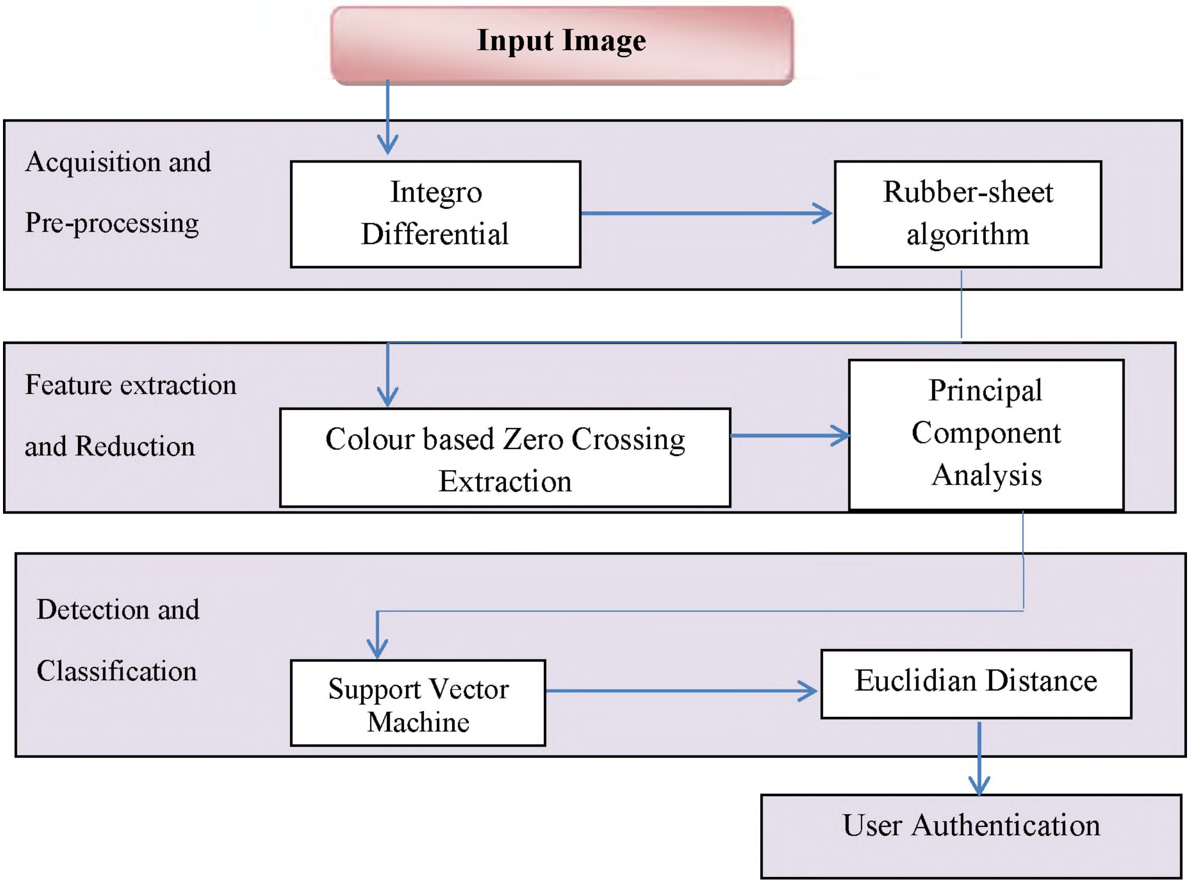


Figure 4.1 Block Diagram of the Proposed Contribution One

To authenticate the mobile device users, a combined approach called PCA-SVMED method is proposed. PCA-SVMED is a combination of Principal Component Analysis (PCA), Support Vector Machine (SVM) and Euclidean Distance (ED).

4.2.1 Acquisition and Pre-processing

The iris input image is captured from various persons by using an android application. The pre-processing of image done using Integro differential operator and Rubber sheet model and is explained below.

4.2.1.1 Integral differential operator

- Integro-differential operators are used to detect the center and diameter of the iris and the pupil respectively.
- These operators exploit both the circular geometry of the iris or the pupil. Indeed, they behave as a circular edge detector since the sclera is always lighter than then iris, and pupil is generally darker than iris for healthy eye.

The Integro-Differential Operator is defined by the equation 4.1

$$max_{(r,x_0 y_0)} = \left| G_\sigma(r) * \frac{\partial}{\partial r} \int_{r,x_0}^{y_0} \frac{I(x,y)}{2\pi r} ds \right| \tag{4.1}$$

where $I(x, y)$ is the Eye image, 'r' is the radius, $G_\sigma(r)$ is a Gaussian Smoothing function, and 's' is the contour of the circle given by $(r, x_0 y_0)$. The operator searches for the circle path where there is maximum change in the pixel avlues by a varying the radius and center 'x' and 'y' position of the circular contour. The integro differential operator is applied iteratively with the amount of smoothing that progressively reduces to attain precise localization . The eyelids are localized with the path of contour integration changed from circular to an arc. The integro-Differential can be seen as a variation of the Hough transform, as it makes use of first derivatives of the image and performs a search to find geometric parameters. The Integero- Differential Operator works with raw derivative infromation .

4.2.1.2 Rubber-Sheet Algorithm

The homogenous rubber sheet model devised by daugman remaps each point within the iris region to a pair coordinates (r, θ) where 'r' is in the interval from 0 to 1 and $'\theta'$ is angle in the interval from $0\ to\ 2\pi$.

The remapping of the iris region from (x, y) cartesian coordinates to the normalized non-cocncentric polar representation is modeled as given by the equations 4.2,4.3 and 4.4

$$I(x(r,\theta), y(r,\theta)) = I(r,\theta) \quad (4.2)$$

with

$$x(r,\theta) = (1-r)x_p(\theta) + rx_1(\theta) \quad (4.3)$$

$$y(r,\theta) = (1-r)y_p(\theta) + ry_1(\theta) \quad (4.4)$$

where $I(x, y)$ is the iris image, (x,y) are the original Cartesian coordiantes, (r, θ) are the corresponding normalized polar coordinates, and the the coordintes of the pupil and the iris boundaries along the θ direction as shown in figure 1.2.

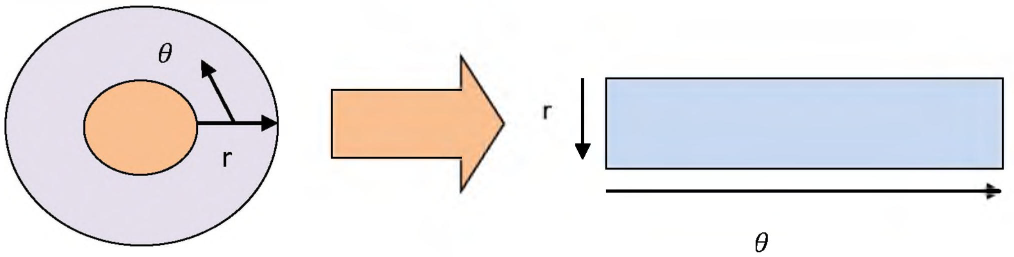


Figure 4.2 Rubber Sheet Model

The rubber sheet model takes into account Pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. The Iris region is modeled as a flexible rubber sheet anchored at the Iris boundary with the Pupil centre as the reference point. The segmented Iris image is normalized to a size $60 * 250$. Then the enhancement are taken by the histogram equalization to brighten and obtain the iris verification.

4.2.2 Feature Extraction and Reduction

After the boundary region of iris, feature of image can be extracted using colour, edge and texture by using Colour based feature extraction and zero crossing method.

4.2.2.1 Color Based Zero-Crossing Extraction

Feature extraction using Color based information of Iris gives the color saturation values which is different for each person. In color based model the color space is used in Iris color segmentation that includes YCbCr, HSV and RGB. Iris Color Image segmentation is computationally inexpensive and is robust to cluttered background.

HSV (hue , saturation and value) color representation is taken because it is compatible with human color perception and it is obtained by the non-linear transformation of fundamental RGB color space. The cone representation of HSV color space is used , where H , S and V are all normalised in the range [0,1]. The H and S components represent the chromatic information, while V represents the luminance information. In this proposed method, two color spaces only namely , HSV and YCbCr are used. The bounding ranges calculated in equation 4.5,4.6 and 4.7 for the values of H, Y , Cb and Cr are used to generate the binary images.

$$R' = R/255$$
$$G' = G/255$$
$$B' = B/255$$
$$Cmax = max(R', G', B') \quad (4.5)$$
$$Cmin = min(R', G', B') \quad (4.6)$$
$$\Delta = Cmax - Cmin \quad (4.7)$$

Hue calculation is defined in equation 4.8,

$$H = \begin{cases} 60° \times \left(\frac{G'-B'}{\Delta} mod6\right), Cmax = R' \\ 60° \times \left(\frac{B'-R'}{\Delta} + 2\right), Cmax = G' \\ 60° \times \left(\frac{R'-G'}{\Delta} + 4\right), Cmax = B' \end{cases} \quad (4.8)$$

Saturation calculation is defined in equation 4.9,

$$S = \begin{cases} 0 & , \Delta = 0 \\ \frac{\Delta}{Cmax} & , \Delta <> 0 \end{cases} \quad (4.9)$$

Value calcuation is define in equation 4.10,

$$V = Cmax \quad (4.10)$$

The zero crossing detector appears for places in the Laplacian of an image where the value of the Laplacian passes through zero. Mostly those points occur at edges in images (i.e. points where the intensity of the image changes rapidly) meanwhile they also occur at places which are not as easy to associate with edges. Here zero crossing detector suits for feature detector rather than as a specific edge detector. Zero crossing always lie on closed contours, and so the output from this is usually a binary image with single pixel thickness lines showing the positions of the zero crossing points.

In 2D image, an x and y derivative will be available. Gradient of the image ΔI is computed as before, but now with DOG kernels for $'x'$ and $'y'$.Then the Zero-crossings of the second derivative now looks at the Laplacian of the image as defined by equation 4.11

$$\Delta I = \frac{\partial^2}{\partial x^2} I(x, y) + \frac{\partial^2}{\partial y^2} I(x, y) \tag{4.11}$$

4.2.2.2 Principal Component Analysis

Principle Component Analysis (PCA) is a statistical procedure

- Uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.
- Reduces the dimensionality of a sample by finding a new set of variables, smaller than the original set of variables that nonetheless retains most of the sample's information.

Let X indicate an N x P data, where N is the number of data samples, which can be regarded as N realizations of a P-dimensional random vector, which has been normalized to zero-mean and unit variance.

It is a linear transformation R^P from, to an M-dimensional vector space, where M≤P . The optimal linear mapping in the least mean square sense is the one formed by the eigenvectors of the correlation matrix of S_X.X is defined in equation 4.12,

$$S_x = \left(\frac{1}{(n-1)}\right) X^T X \tag{4.12}$$

Let Z denote the N × M transformed data matrix. The PCA transforms X to Z by the following equation

$$Z = XV_M \tag{4.13}$$

where V_M refers to the P×M weight matrix, consists of eigenvectors corresponding to the first largest eigen values of the correlation matrix S_X , or V_M corresponds to the first M column vectors of matrix, which is obtained through Singular Value Decomposition (SVD) of a scaled matrix is defined in 4.14

$$T=(\ 1\sqrt{(N-1)}\ )\ X=UDV^T \quad (4.14)$$

Here, both U and V are unitary matrices, and D is a P×P diagonal matrix with nonnegative diagonal elements d_i in decreasing order.

Evaluating the statistical significance of a Principal Component (PC) is a significant part of choosing an accurate dimension for PCA to capture the most relevant features. As they are mutually uncorrelated, each coefficient is tested individually using only one random variable statistics to determine whether it is relevant or random.

4.2.3 Detection and Classification

After the features are extracted and reduced, the template matching with minimum distance calculation between the features and Support Vector Machine structure is done by using SVMED algorithm which is explained below.

4.2.3.1 Support Vector Machine with Euclidean Distance

For an supervised binary classification problem in Support Vector Machine, the training data are represented by $\{x_i, y_i\}, i = 1,2,\dots,N$ and $y_i \epsilon \{-1,+1\}$, where N is the number of training samples, $y_i = +1$ for class ω_1 and $y_i = -1$ for class ω_2.

Suppose the two classes are linearly separable, it is possible to find at least one hyperplane defined by a vectorwith a bias w_0 , which can separate the classes without error. The function is defined by equation 4.15

$$f(x) = w.x + w_0 \quad (4.15)$$

To find such a hyperplane, w and w_0 should be estimated in a way that $y_i(w.x_i + w_o) \geq +1$ for $y_i = +1$ (class ω_1) and $y_i(w.x_i + w_o) \leq -1$ for $y_i = -1$ (class ω_2). These two can be combined to provide equation 4.16:

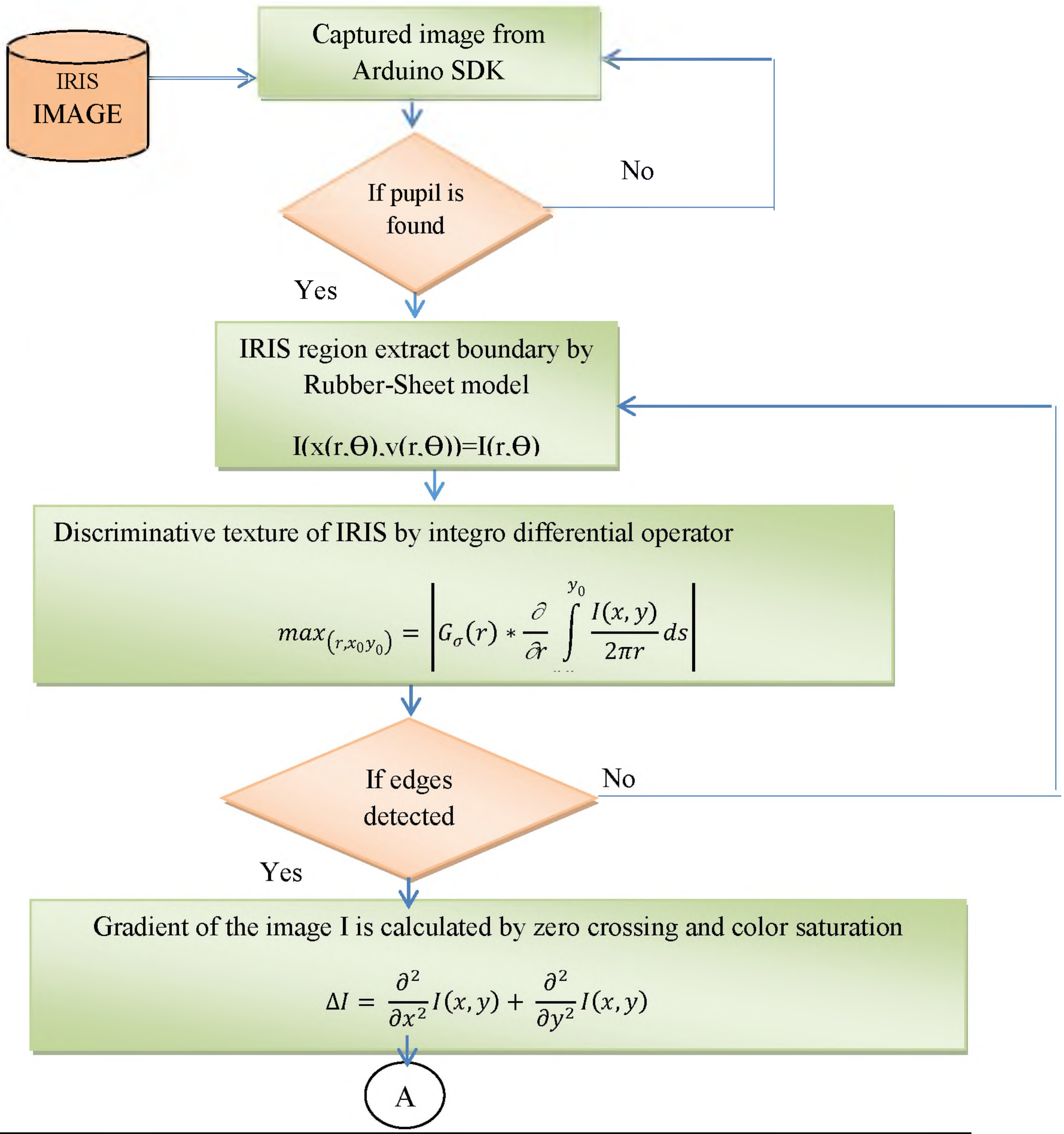
$$y_i(w.x_i + w_0) - 1 \geq 0 \quad (4.16)$$

This euclidean distance measurement technique used here is to find out the minimum distance between the feature and the Support Vector Machine structure.The Euclidean distance between the points P and Q is the length connecting between them. In cartesian coordiantes if $P = (P_1, P_2, \ldots, P_n)$ and $Q = (Q_1, Q_2, \ldots, Q_n)$ are two points in Euclidean n-space, then the distance from P to Q or from Q to P is given by the equation 4.17.

$$d(P,Q) = \sqrt{(Q_1 - P_1)^2 + (Q_2 - P_2)^2 + \cdots + (Q_n - P_n)^2} = \sqrt{\sum_{i=1}^{n}(Q_i - P_i)^2} \tag{4.17}$$

4.3 Flow diagram of the Proposed Contribution One – PCA-SVMED Method

The proposed method PCA-SVMED authenticates the user of mobile device using Principal Component Analysis (PCA) with Support Vector Machine (SVM) and distance measurement using Euclidean Distance (ED). The flow diagram of the proposed contribution one is shown in figure.4.2



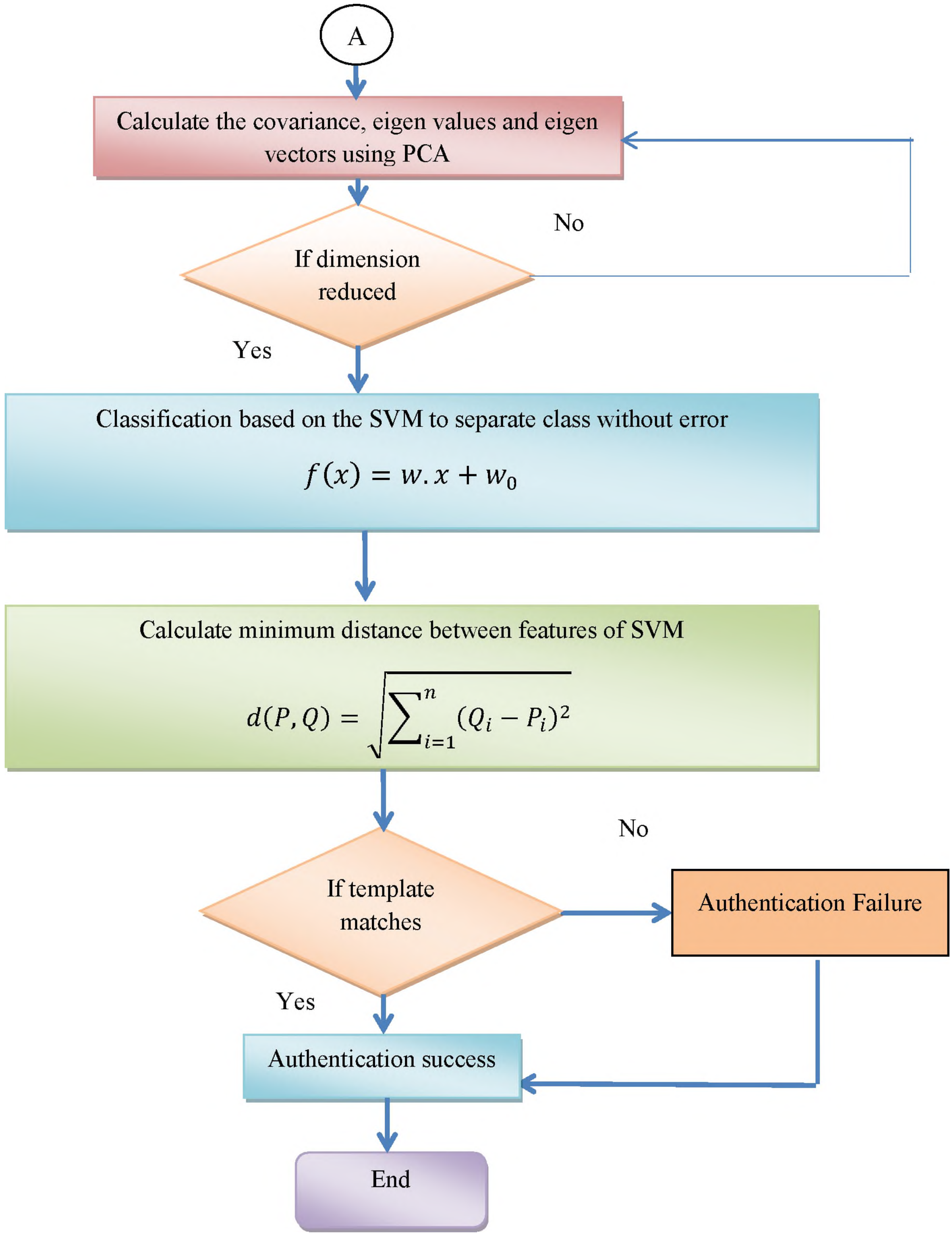


Figure 4.3 Flow Chart of Proposed PCA-SVMED Method

4.4 Steps involved in the Proposed PCA-SVMED Method

The steps used for the process of authentication using iris biometric is discussed below:

Step 1: *Capture iris image I, using the android app in mobile device and pupil is detected.*

Step 2: *Apply Rubber Sheet model for region boundary extraction by the following equation.*

$$I(x(r,\Theta),y(r,\Theta))=I(r,\Theta)$$

Step 3: *Apply Integro differential operator for discriminative texture analysis*

$$max_{(r,x_0y_0)} = \left| G_\sigma(r) * \frac{\partial}{\partial r} \int_{r,x_0}^{y_0} \frac{I(x,y)}{2\pi r} ds \right|$$

Step 4: *Construct gradient of image I calculated by zero crossing. Feature vector extraction of gradient image and the colour saturation of HSV representation of image I by the following equation.*

$$\Delta I = \frac{\partial^2}{\partial x^2} I(x,y) + \frac{\partial^2}{\partial y^2} I(x,y)$$

$$H = \begin{cases} 60^\circ \times \left(\frac{G' - B'}{\Delta} mod6 \right), Cmax = R' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2 \right), Cmax = G' \\ 60^\circ \times \left(\frac{R' - G'}{\Delta} + 4 \right), Cmax = B' \end{cases}$$

$$S = \begin{cases} 0 & , \Delta = 0 \\ \frac{\Delta}{Cmax} & , \Delta <> 0 \end{cases}$$

$$V = Cmax$$

Step 5: *Apply PCA algorithm for the feature dimension reduction of image by calculating covariance matrix, Eigen values and Eigen vectors*

Step 6: *Apply SVM classification for template matching and to separate classes without error by following equation.*

$$f(x) = w.x + w_0$$

Step 7: *Calculate the Euclidean distance for template matching and authentication of mobile device.*

Seven steps discussed above are followed to authenticate the mobile device user. The algorithm proposed is discussed below.

4.5 Pseudo code of PCA-SVMED Method

The algorithmic procedures applied for Mobile Device Authentication by the proposed method PCA-SVMED shown in table 4.1 below.

Table 4.1 Pseudo code of PCA-SVMED Method

```
for iris image I input gradient of training image
    assign linear transformation Av=b
        b and v=vector, A=matrix
  for covariance matrix numpy.cov() inbuilt
        eigen vector are identical to covariance matrix
                assert eigenvalue == eigencov.all
            eigen vector and eigen values are assigned rows and columns
                EigenVectorAsColumn()
                EigenValueAsRow()
  End
  SVM classification by testing image Row () and Column ()
Linear separating hyperplane classification
    if {the pattern exists in the iris DB:  Output the matching result (Authenticate the user)
} else
enroll the feature vector in the iris DB.
    End
End
```

4.6 Experimental Setup and Results

In the experimentation, the captured iris images are pre-processed and features are reduced using the PCA algorithm. The template matching of iris biometric for mobile device authentication is classified using SVM. The minimum distance between the feature and structure of SVM are calculated using Euclidian Distance. For validation of proposed method, iris images are captured using an android application and authenticated using the proposed methodology. A few sample of iris images captured for experimentation is shown in Annexure I.

The proposed PCA-SVMED method is implemented. The experimentation methodology is shown in figure 4.4.

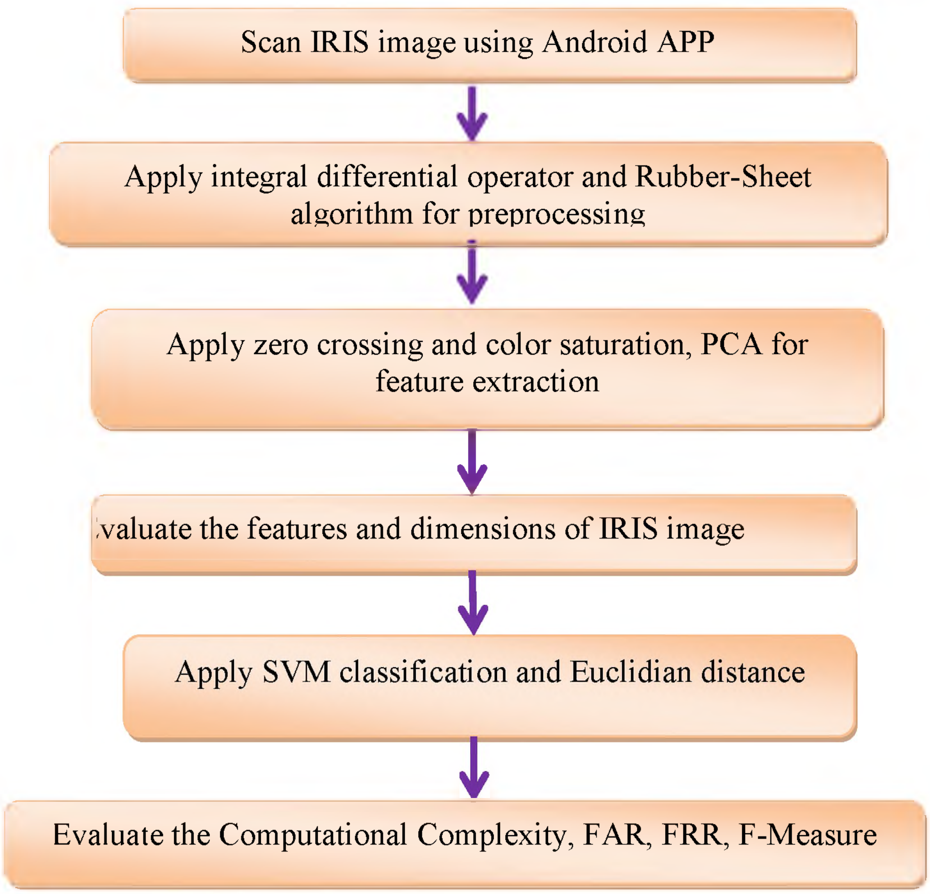


Figure 4.4 Experimentation Methodology for Contribution One

To evaluate the performance of the proposed method, the following five parameters listed below are used and defined:

i. False acceptance rate
ii. False rejection ratio
iii. Accuracy
iv. Computational complexity
v. F-Measure

i. False Acceptance Rate

The false acceptance ratio is a unit used to measure the average number of false acceptances within a biometric security system. It measures and evaluates the efficiency and accuracy of a biometric system by determining the rate at which unauthorized or illegitimate users are verified on a particular system. It is calculated by the equation 4.18.

$$FAR = \frac{Number\ of\ false\ acceptances}{Number\ of\ total\ imposter\ attempts} \tag{4.18}$$

The False Accept Rate (FAR) is the percentage of authentication decisions that allow access to an unauthorized user.

ii. False Rejection Ratio

The False Rejection Rate is the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent are of valid inputs which are incorrectly rejected and it is calculated by the equation 4.19.

$$FRR = \frac{Number\ of\ false\ rejections}{Number\ of\ total\ authentic\ attempts} \tag{4.19}$$

The False Reject Rate (FRR) is the percentage of authentication decisions where an authorized user is denied access.

iii. Accuracy

Authentication accuracy indicates the possibility of correctly identifying an individual (including both imposters and legitimate users). Accuracy calculated by the equation 4.20.

$$Accuracy = \frac{TP + TN}{(TP+TN+FP+FN)} \tag{4.20}$$

Here,True positive is correctly identified, False positive is incorrectly identified, True negative is correctly rejected and False negative is incorrectly rejected where TP is the Number of True Positive Instances, FN is the Number of False Negative Instances, FP is the Number of false Positive Instances, TN is the Number of True Negative Instances.

iv. Computational complexity

It is the time required to complete the whole process of an system. This is usually available in seconds or mili seconds. If the system takes much time, then the system is considered as complex system. It is defined by equation 4.21.

$$T(x) = \sum_{i=1}^{n-1} \sum_{j+1}^{n} \sum_{k=i}^{j} c = c \sum_{i=1}^{n-1} \sum_{j+1}^{n} (j - i + 1) \tag{4.21}$$

v. F-measure

This measure computes the harmonic mean of precision and recall and is called as F-measure. Given n points, x^1, x^2..., x^n, the harmonic mean is defined in equation 4.22

$$\frac{1}{H} = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{x_i} \tag{4.22}$$

The F-measure or balanced f-score is defined in equation 4.23,

$$F = 2. \frac{precision.recall}{precision+recall} \tag{4.23}$$

Table 4.1 shows the comparison of the results of the proposed method with existing SVMED in terms of the above defined parameters. The results obtained for various samples with their mean total is given in Table 4.2.

Table 4.2 Performance comparison of Authentication Results for Existing SVMED with Proposed PCA-SVMED Method

Methods / Parameters	SVMED	PCA-SVMED	% of Improvement
Computational Complexity (ms)	53	50	**3**
F-measure	5.67	5.35	**0.32**
FAR (%)	0.0311	0.0225	**0.0085**
FRR (%)	0.0335	0.0235	**0.007**
Accuracy (%)	95	97	**2**

Figure 4.5 gives the Computational Complexity comparison between existing Zero Crossing with SVM-ED and proposed PCA - Zero Crossing with SVM-ED. From Figure 4.5, it is clearly observed that the proposed PCA - Zero Crossing with SVM-ED provides improved 3ms result, that is less than existing method.

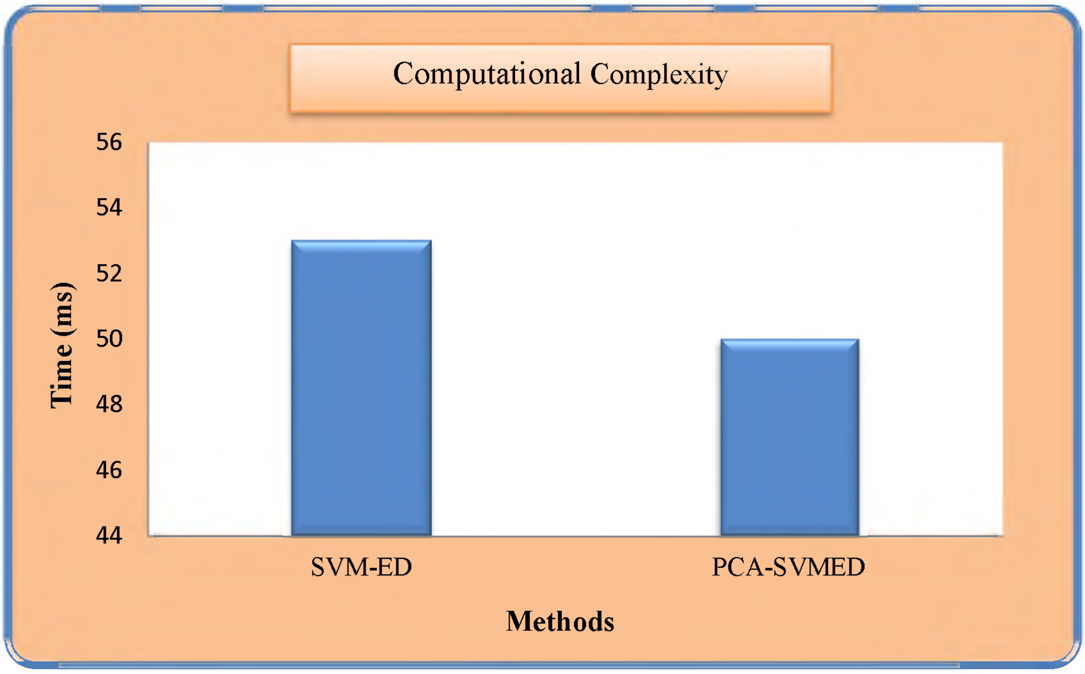


Figure 4.5 Comparision of Computational Complexity in terms of Time for Contribution One

Figure 4.6 and Figure 4.7 illustrate the comparison between FAR and FRR for existing SVMED and proposed PCA-SVMED. It can be clearly observed that the proposed method PCA-SVMED gives better results compared to the existing method.

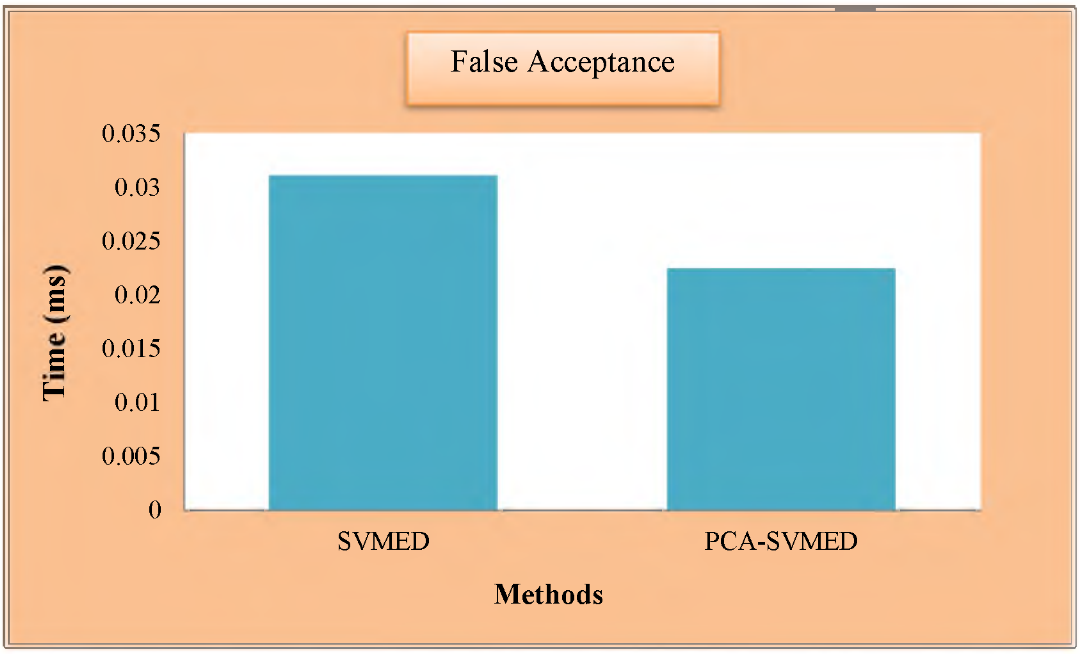


Figure 4.6 Comparison of False Acceptance Rate for Contribution One

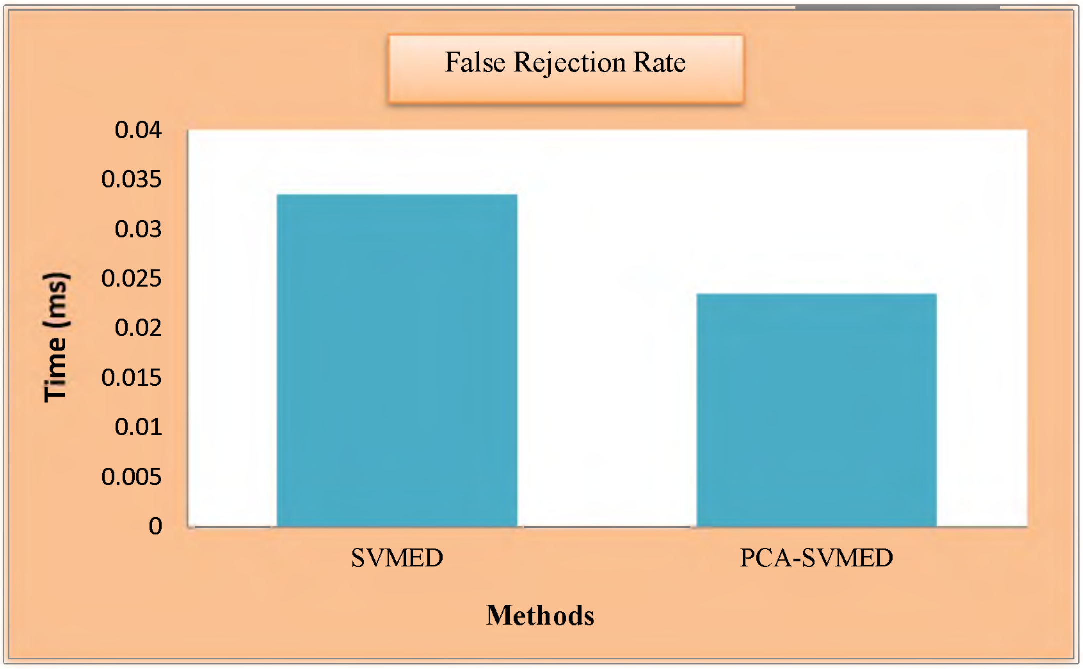


Figure 4.7 Comparision of False Rejection Rate for Contribution One

Overall accuracy is shown in Figure 4.8 for existing SVMED and proposed PCA-SVMED. In this, accuracy attained by existing SVMED is 95 % and proposed PCA-SVMED is 97 %.

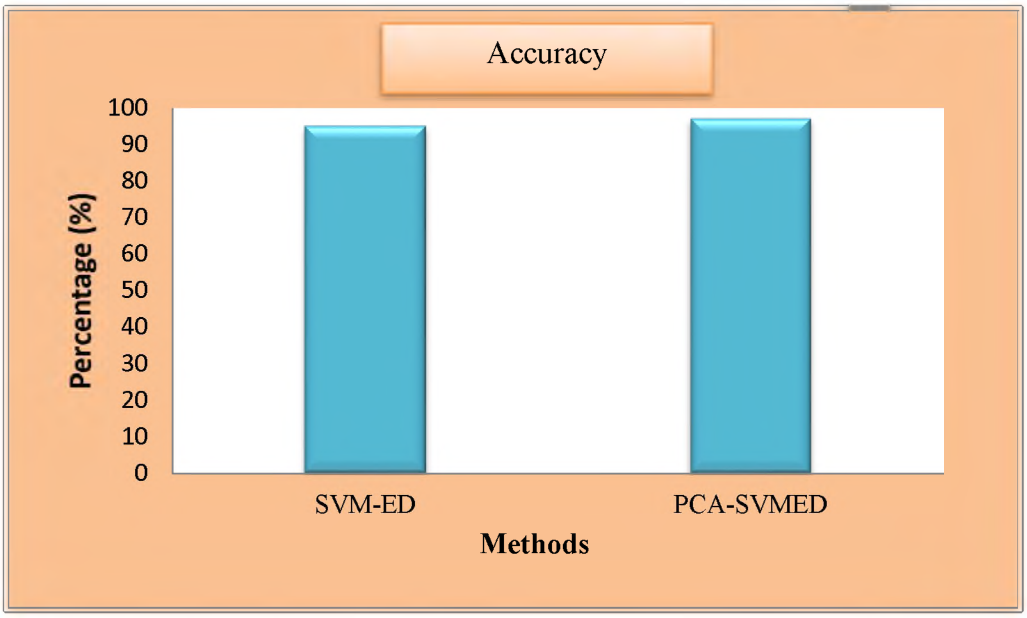


Figure 4.8 Comparision of Results for Accuracy for Contribution One

The F-measure value for existing SVMED and proposed PCA-SVMED is shown in Figure 4.9.

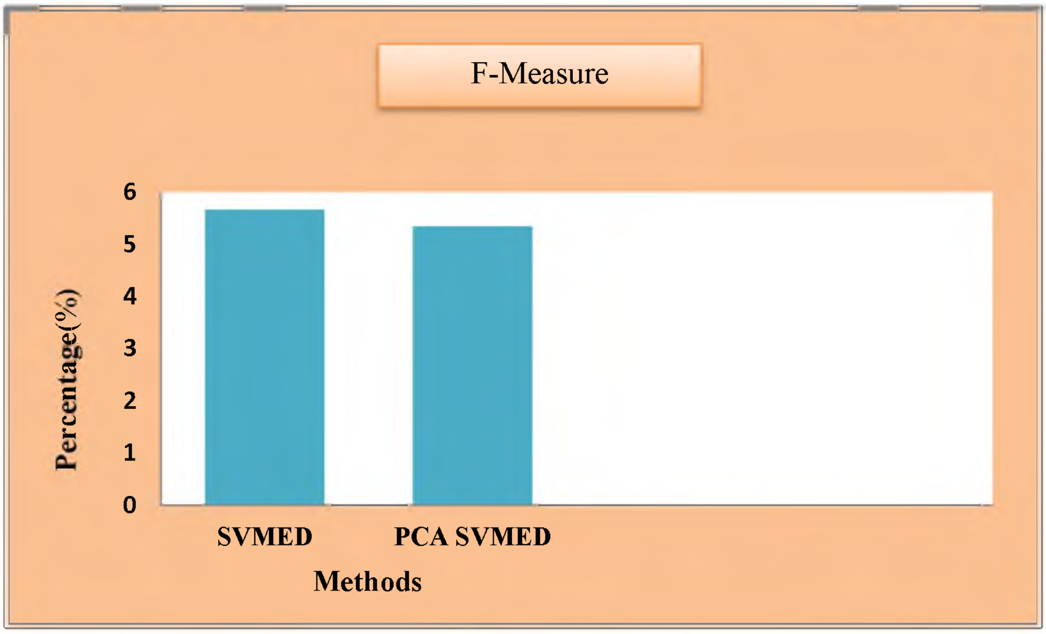


Figure 4.9 Comparision of F- Measure for Contribution One

4.7 Chapter Summary

In this chapter, an enhanced mobile device authentication is proposed using iris biometric. The classified iris image ensures the accurate user authentication in mobile devices. The experimental results show on the recognition accuracy of 97% during detection and classification of iris biometric authentication with minimal computational complexity in terms of time and improved accuracy. The unauthorized access to the mobile device is detected in single biometric system and false detection rate is reduced. Improved and accurate user authentication using PCA-SVMED method is efficiently deployed. The next possible threat on mobile devices is malicious applications. To detect the presence of malware in mobile devices, Contribution two is proposed and explained in chapter 5.