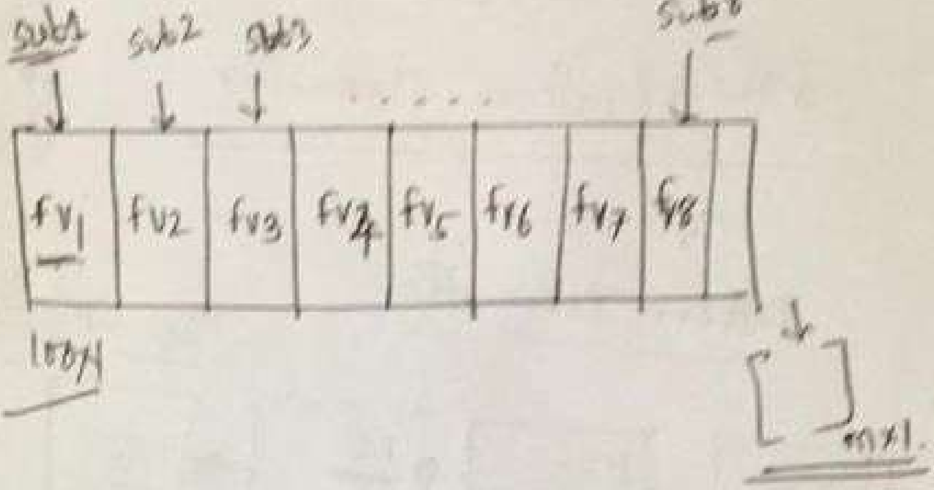
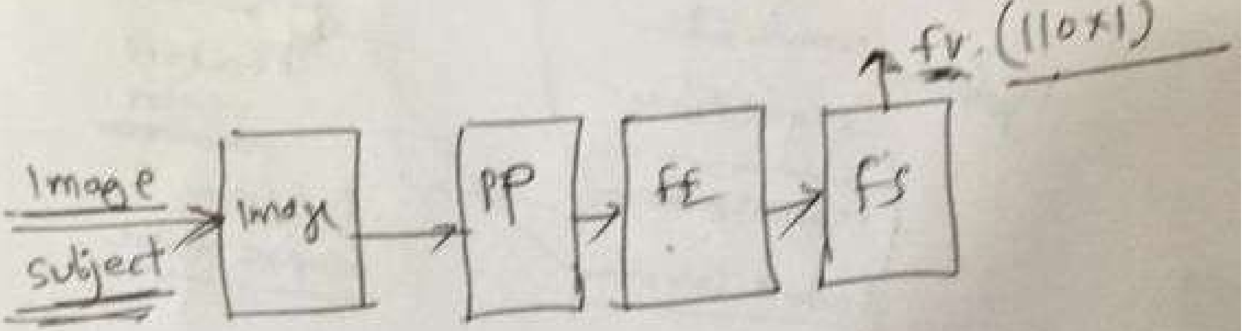




Testing

Size of fv generated during Testing is similar to fv1 ... fv8.

* find comparison / match.

Comparison is carried out using classifier

Algorithm

Various Thresholds

Th1

Th2

Th3

.

.

.

distance Threshold changes the Accuracy

You can decide a unique value of Threshold for which Algorithm furnishes maximum Accuracy

$$fv_1 = fv$$

$$\cancel{fv_1} \quad fv_1 = \begin{bmatrix} 1 \\ 2 \\ 5 \\ 7 \\ 9 \end{bmatrix}$$

$$fv = \begin{bmatrix} 1 \\ 1.8 \\ 5.1 \\ 6.8 \\ 9 \end{bmatrix}$$

$$d = \frac{1}{5}\sqrt{(1-1)^2 + (2-1.8)^2 + (5-5.1)^2 + (7-6.8)^2 + (9-9)^2}$$

$$d = 0 + 0.2 + (-0.1) + 0.2 + 0$$

$$d = 0.2 - 0.1 + 0.2$$

$$d = 0.3 \checkmark$$

$$fv \neq fv_1 \; ; \; \boxed{d \leq \text{Threshold}}$$

$$\boxed{\text{Threshold} = \cancel{0.3}\ 0.2}$$

Subject 1

$$\boxed{\text{subject} = \text{subject } 1}$$

classier/classification

un-supervised
(Training not required)

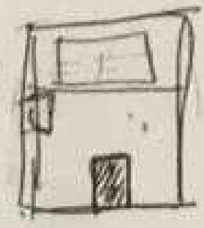
distance classifier

Types
→ ED (L_1-norm / L_2 norm)
→ MD (mahalobonis distance)

supervised
(need training)
learning

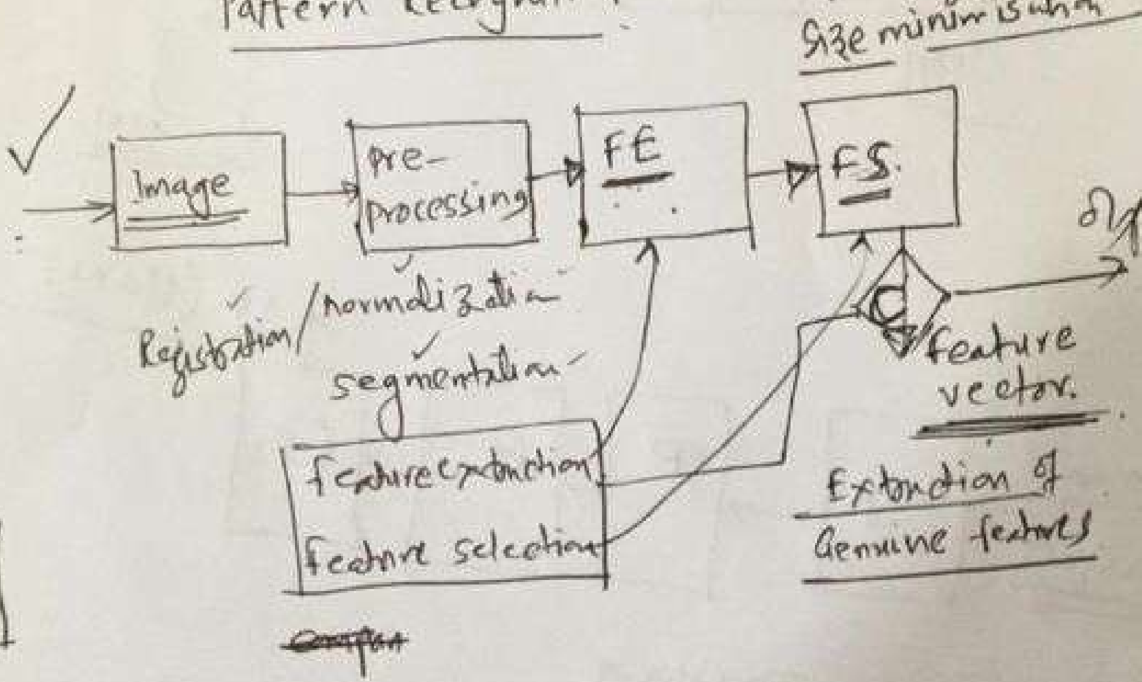
1. Neural Network
2. Deep learning Network.
3. Support vector machine (SVM)
4. Probability (Maximum liklihood Estimate) (MLE).

semi-supervised



Image/pattern Classifier

Pattern Recognition



feature vector — column vector

- → Training ← stored the FV of subjects in database
- → Testing → Determine FV of subject and compare with FVs which are stored in the database.

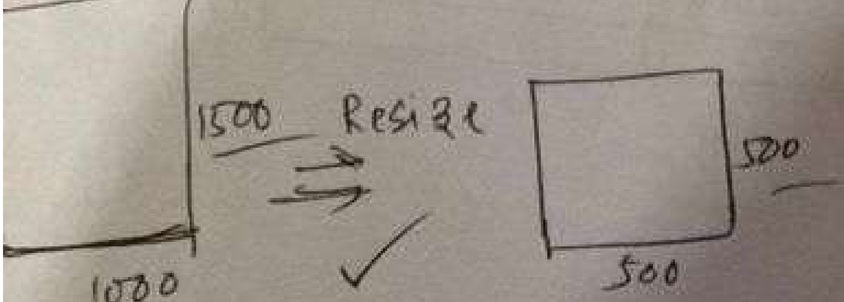


Image Classification

→ False Acceptance Rate

→ False Rejection Rate.

→ if N number of subjects with 8 images each.

Total images $= T = N \times 8 = 10 \times 8 = 80$

→ Total no. of comparisons are

$N \times (T-1) = 10 \times (80-1) = 10 \times 79 = 790$

out of which the true claims/Genuine claims

$= N \times 7$

→ False rejection Rate (FRR) $= \dfrac{\text{true claims rejected}}{\text{total true claims}} \times 100$

→ False Acceptance Rate (FAR) $= \dfrac{\text{Imposter claims accepted}}{\text{total imposter claims}} \times 100$

→ Genuine Acceptance Rate (GAR) $= 1 - FRR$

11.6 Minimum Distance Classifier

The **minimum distance classifier** is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Figure 11.6.1 shows the concept of a minimum distance classifier. The following distances are often used in this procedure.

(1) Euclidian distance

$$d_k^2 = (X - \mu_k)^t (X - \mu_k)$$

Is used in cases where the variances of the population classes are different to each other. The Euclidian distance is theoretically identical to the similarity index.

(2) Normalized Euclidian distance

The Normalized Euclidian distance is proportional to the similarity in dex, as shown in Figure 11.6.2, in the case of difference variance.

$$d_k^2 = (X - \mu_k)^t \sigma_k^{-1} (X - \mu_k)$$

(3) Mahalanobis distance

In cases where there is correlation between the axes in feature space, the Mahalanobis distance with variance-covariance matrix, should be used as shown in Figure 11.6.3.

$$d_k^2 = (X - \mu_k)^t \Sigma_k^{-1} (X - \mu_k)$$

where **X** : vector of image data (n bands)

X = [x1, x2, ... xn]

μk : mean of the kth class

μk = [m1, m2, ... mn]

σk : variance matrix

$$\sigma_k = \begin{bmatrix} \sigma_{11} & 0 & \cdots & 0 \\ 0 & \sigma_{22} & & 0 \\ \vdots & & \ddots & \\ 0 & \cdots & \cdots & \sigma_{nn} \end{bmatrix}$$

Σk : variance-covariance matrix

$$\Sigma_k = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix}$$

Figure 11.6.4 shows examples of classification with the three distances.

ED —

$$d_k^2 = (X - \mu_k)^T \cdot (X - \mu_k)$$

X – feature vector

μ_k – Mean of k^{th} class

or simply

$$d = \sqrt{(p_1 - p_2)^2 + (q_1 - q_2)^2}$$

———— x ————

MD —

$$d_k^2 = (X - \mu_k)^T C^{-1} (X - \mu_k)$$

C is covariance

$$C = \frac{\sum_{i=1}^{n} (X - \mu_x)(Y - \mu_y)}{n-1}$$

ED —

$$d_k^2 = (x - \mu_k)^T \cdot (x - \mu_k)$$

x – feature vector

μ_k – Mean of k^{th} class

or simply

$$d = \sqrt{(p_1 - p_2)^2 + (q_1 - q_2)^2}$$

———— x ————

MD —

$$d_k^2 = (x - \mu_k)^T C^{-1} (x - \mu_k)$$

C is covariance

$$C = \frac{\sum_{i=1}^{n} (x - \mu_x)(Y - \mu_y)}{n-1}$$