Q/

(a) Definication of generative & descriminative classifier [0.5 m]

GMM ← generative } with justification [0.5 m]
SVM ← descriminative }

(b) Training procedure SVM & GMM [1 m]

yes, can able to handle (with justification) [1 m]

(c) Bennolli distribusction is preffered as
binary data . (with appropriate justification) [1 m]

(d) Refer in Bishop (Pattern Recognition & machine learning book)
page no. (444-445).

eq^n 9.44 , 9.48 , 9.56 , 9.57, 9.58
9.54, 9.60 , 9.51   is
                    empected [2 m]

(e) $X = \begin{bmatrix} 0 & 1 \\ 0 & 1 \end{bmatrix}$, $\lambda_1 = [0.3, 0.6, 0.6, 0.6]$
                    $\lambda_2 = [0.1, 0.8, 0.6, 0.1]$

$$P(X/\lambda_1) = \prod_{i=1}^{4} (\lambda_{1i})^{x_i} (1-\lambda_{1i})^{1-x_i} \quad \text{0.5}$$

$$= 0.7 \times 0.6 \times 0.4 \times 0.6 = 0.1008$$

$$P(X/\lambda_2) = \prod_{i=1}^{4} (\lambda_{2i})^{x_i} (1-\lambda_{2i})^{1-x_i} \quad \text{0.5}$$

$$= 0.9 \times 0.8 \times 0.4 \times 0.1$$
$$= 0.0288$$

As. priors are equiprobable,
and $P(X/\lambda_2) < P(X/\lambda_1)$
                    0.5

X is belongs to λ_1 class
                    2 m

2) (a)
We need dimensionality reduction :-
(i) When we deal with real data we often deal
with high dimensional data that can go upto
millions. But these dimension can be highly
correlated in itself. Hence, we can reduce
to lower dimension. This will speed by
the computation.

(ii)

Pros	Cons
i) Removes correlated features.	i) Information is lost.
ii) Reduces overfitting & improves visualization	ii) Independent variables becomes less interpretable.

— ① marks

Steps to dimensionally reduce using PCA :-

1) Pre-processing :
    Stack 64×64 image matrix into 1 column.
    Mean and variance normalization.
    $$\Rightarrow data = data - mean(data) ;$$

2) Construct covariance matrix

3) Decompose the covariance matrix into
    eigenvectors & eigenvalues

4) Sort the eigenvalues in decreasing order to
    rank corresponding eigenvectors.

5) Select k eigenvectors which correspond to
    the k- largest eigenvalues.

6) Construct a projection matrix W from "top" k eigenvectors.

7) Transform the d-dimensional input dataset X using the projection matrix W to obtain the new k-dimensional feature subspace.

— ① marks

Steps of dimensionality reduction using LDA.

1) Compute d-dimensional mean vector for different classes from the dataset.

2) Compute the "in between class" & "within-class matrix".

3) Compute the eigenvectors $(e_1, e_2, -, ed)$ & corresponding eigenvalues $(\lambda_1, \lambda_2, ---, \lambda_d)$

4) Sort the eigenvectors by decreasing eigenvalues and choose k - eigenvectors with the largest eigenvalues to form d×k dimensional matrix W

5) Use this d×k eigenvector matrix to transform the samples onto the new subspace.

$$Y = X \times W$$

n×k   n×d   d×k

$k < < d$

— ① marks

2)(b) Difference b/w   LDA & PCA   — (1) marks

@ To measure the performance we can apply the reverse transformation and measure the reconstruction error.

~~Also the performance can~~

If dimensionality reduction is used as preprocessing step before another ML algorithm, then we can simply measure the performance of the second algorithm. If dimensionality reduction did not loose too much information, the ~~se~~ second algorithm should perform well.

Note:- Multiple solutions are allowed.

2)(c) -
                                    — 1 marks

It is not possible to perfectly reverce the operation because some information gets lost during dimensionality reduction.

                                    1 marks

4)   Multiple solutions are accepted.

Method   — 1 marks

Training with block diagram   - 2 marks

Testing with appropriate block diagram - 2 marks

Entropy $H(s) = \sum_{i=1}^{N} -p_i \log_2 (p_i)$

Information Gain $IG(s, A) = H(s) - H(s|A)$

1] $H(Disease) = -\left(\frac{9}{14}\right) \log_2 \left(\frac{9}{14}\right) - \left(\frac{5}{14}\right) \log_2 \left(\frac{5}{14}\right) = \cdot 0.94$

2] Entropy for Disease for each condition of ~~cough~~ fever

$H(D | F = Absent) = -\frac{2}{4} \log_2 \left(\frac{2}{4}\right) - \frac{2}{4} \log_2 \left(\frac{2}{4}\right) = \cdot 1$

$H(D | F = mild) = -\frac{4}{6} \log_2 \left(\frac{4}{6}\right) - \frac{2}{6} \log_2 \left(\frac{2}{6}\right) = \cdot 0.92$

$H(D | F = severe) = -\frac{3}{4} \log_2 \left(\frac{3}{4}\right) - \frac{1}{4} \log_2 \left(\frac{1}{4}\right) = \cdot 0.81$

Weighted Entropy

$H(D | F) = \frac{4}{14} \times 1 + \frac{6}{14} \times 0.92 + \frac{4}{14} \times 0.72 = 0.91$

$IG(D, F) = 0.94 - 0.91 = 0.03$

3] Entropy for Disease for each condition of cough

$H(D | C = Absent) = -\frac{2}{5} \log_2 \left(\frac{2}{5}\right) - \frac{3}{5} \log_2 \left(\frac{3}{5}\right) = 0.97$

$H(D | C = mild) = -\frac{4}{4} \log_2 \left(\frac{4}{4}\right) - \frac{0}{4} \log_2 \left(\frac{0}{4}\right) = 0$

$H(D | C = severe) = -\frac{3}{5} \log_2 \left(\frac{3}{5}\right) - \frac{2}{5} \log_2 \left(\frac{2}{5}\right) = 0.97$

Weighted entropy

$H(D | C) = \frac{5}{14} \times 0.97 + \frac{4}{14} \times 0 + \frac{5}{14} \times 0.97 = 0.69$

$IG(D, C) = 0.94 - 0.69 = 0.25$

4y $IG(D, J) = 0.152$

    $IG(D, g) = 0.048$

Cough has larger entropy gain.

∴ forms the root node.

    If cough = Mild, Disease = True

    ∴ No need to split further. (entropy = zero)

$H(Fever) =$

$H(Absent) = -\left(\dfrac{2}{5}\right)\log\left(\dfrac{2}{5}\right) - \left(\dfrac{3}{5}\right)\log\left(\dfrac{3}{5}\right) = 0.97$

$H\left(\text{cough = Absent}\Big/\text{fever}\right) = 0.4$

$IG\left(\text{cough = Absent}\Big/\text{fever}\right) = 0.571$

4y

$IG\left(\text{cough = Absent}\Big/\text{Travel}\right) = 0.971$

$IG\left(\text{cough = Absent}\Big/\text{Gender}\right) = 0.020$

split based on Travel.

```
                    ┌─────────┐
                    │  Cough  │
                    └─────────┘
              ↙          ↓          ↘
          Absent        Mild         Severe
            │            ↓             │
            ↓           Yes            ↓
        ┌────────┐              ┌──────────┐
        │ Travel │              │  Gender  │
        └────────┘              └──────────┘
          ↙    ↘                   ↓      ↘
        No     Yes              Male     Female
         ↓      ↓                ↓         ↓
        No     Yes              No        Yes
```