Chapter 9 **Object Recognition**

Introduction

Classification or Learning of an Image or Decision Theoretic Methods

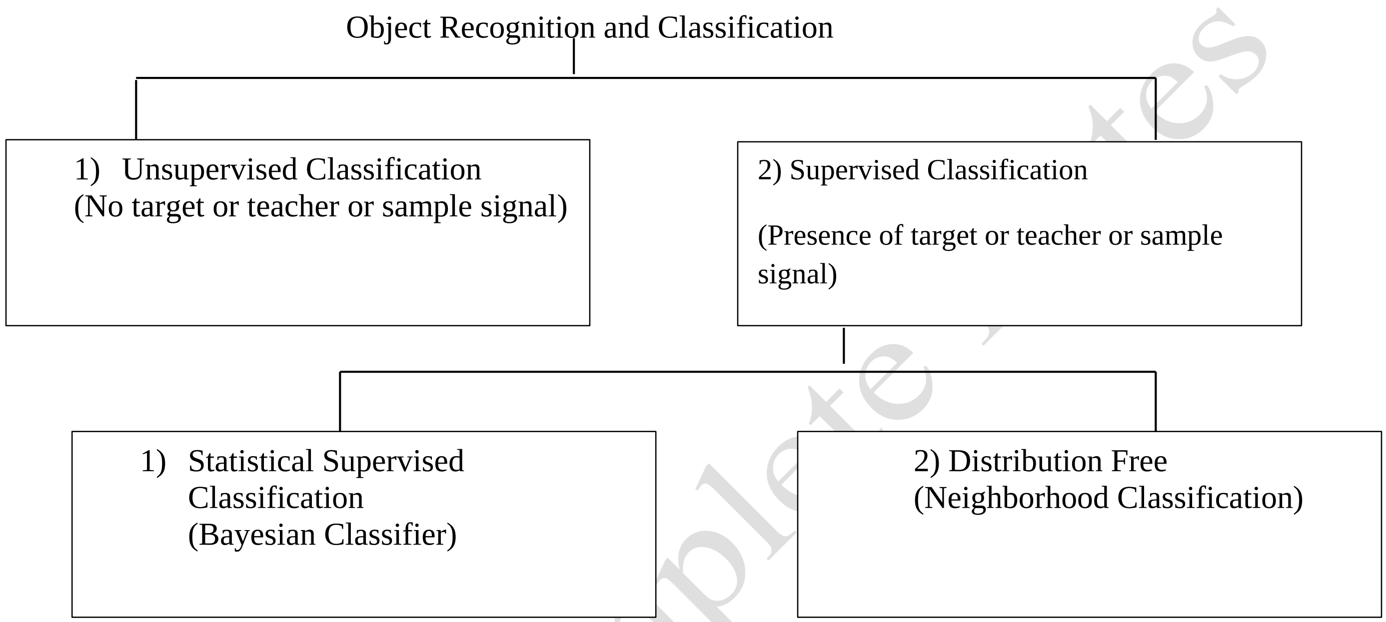


Figure 9.1: Decision Theoretic Methods

- The approaches to pattern recognition developed are divided into two principal areas: decision-theoretic and structural .The first category deals with patterns described using quantitative descriptors, such as length, area, and texture. The second category deals with patterns best described by qualitative descriptors, such as the relational descriptors.
- Basic pattern recognition flowchart

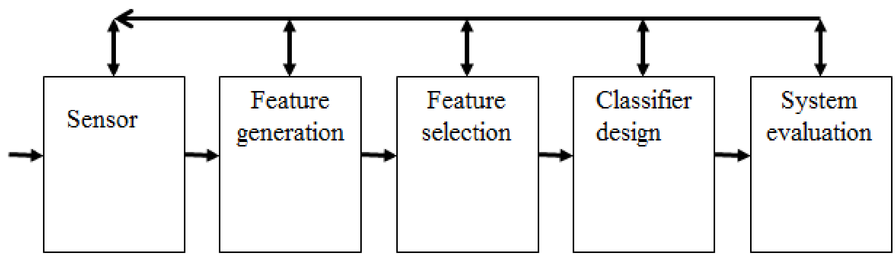


Figure 9.2 Pattern Recognition Flowchart

1) Unsupervised Classification

A very common task concerning in image processing is classification which is done in order to use the image for mapping or further analysis.

In unsupervised classification learning, there is no teacher or target or sample signal in the same way, it is also computerized method without direction of analysis. It means that the output are based on software without providing user signal or sample classes. The computer uses the technique to determine which pixel is detected and what classes belongs together.

In this technique the user or human doesn't interface to the unsupervised classification. Cluster is one of the unsupervised learning technique or classification. For unsupervised classification, the figure shows the techniques of object recognition.

101	105	105	105
101	101	105	105
103	101	101	101
103	103	101	101

Input Image

B	C	C	C
B	B	C	C
A	B	B	B
A	A	B	B

B	C	C	C
A	B	C	C
A	A	B	C
A	A	A	B

Class Classification

Figure 9.3: Example of Unsupervised learning or classification using clustering technique.

Where A=Water   B=Land   C=Rock

2) Supervised Classification

In Supervised classification, it doesn't use the computer software to create the classes. Here the analysis identifies the several areas in an image which represents different futures. These known areas are referred to as Training site. The computer only does the assignment of pixel to the classes. It is based on the idea that a user can select sample pixel or target signal in an image i.e. representative of specific classification it means that the provided user signal or teacher signal can help to make the classification without using computer tools

Supervised classification is categorized into two types

(i) Statistical Supervised Classification

(ii) Distribution Free

9.1 Pattern and Pattern Classes

A pattern is an arrangement of descriptors. The name feature is used often in the pattern recognition literature to denote a descriptor. A pattern class is a family of patterns that share some common properties. Pattern classes are denoted by W_1, W_2,W_3,…….W_W where W is the number of classes. Pattern Recognition by machine involves techniques for assigning pattern to their respective classes W automatically and with as little human intervention as possible.

Object or pattern recognition task consists of two steps:

- Feature selection(extraction)
- Matching(classification)

Three common pattern arrangements used in practices are

(a)Numeric Vectors

(b) Strings

(c) Trees

(a) **Numeric Vectors**

Numeric vectors (for quantitative descriptions).

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

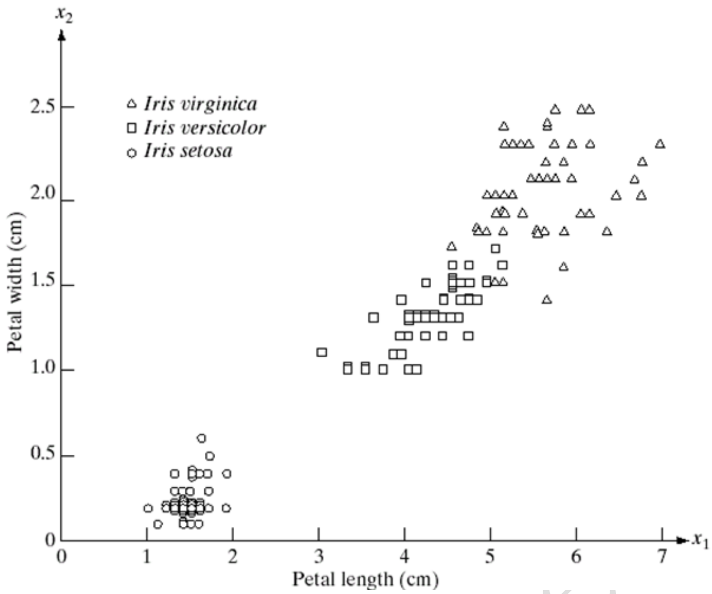
Historical Example:

Recognition of three types of iris flowers by the lengths and widths of their petals (Fisher 1936).

• Variations between and within classes.

• Class separability depends strongly on the choice of descriptors.

Three types of iris flowers described by two measurements.



Here is **another example** of pattern vector generation.

In this case, we are interested in different types of noisy shapes.

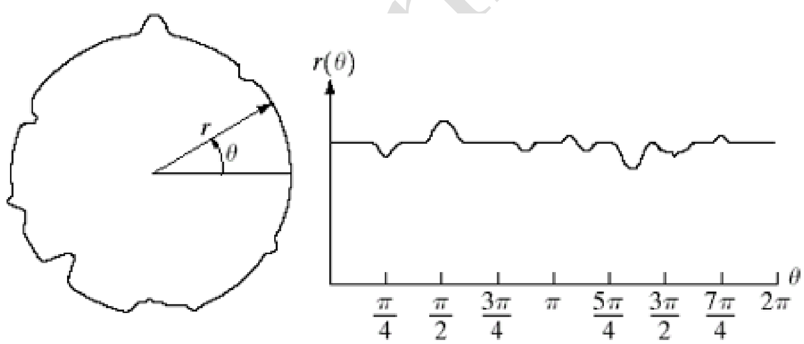


Figure 9.4 A noisy object and its corresponding signature.

(b) Strings descriptions adequately generate patterns of objects and other entities whose structure is based on relatively simple connectivity of primitives, usually associated with boundary shape.

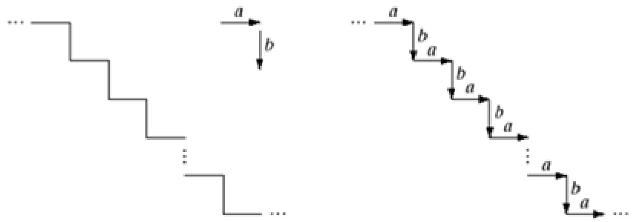
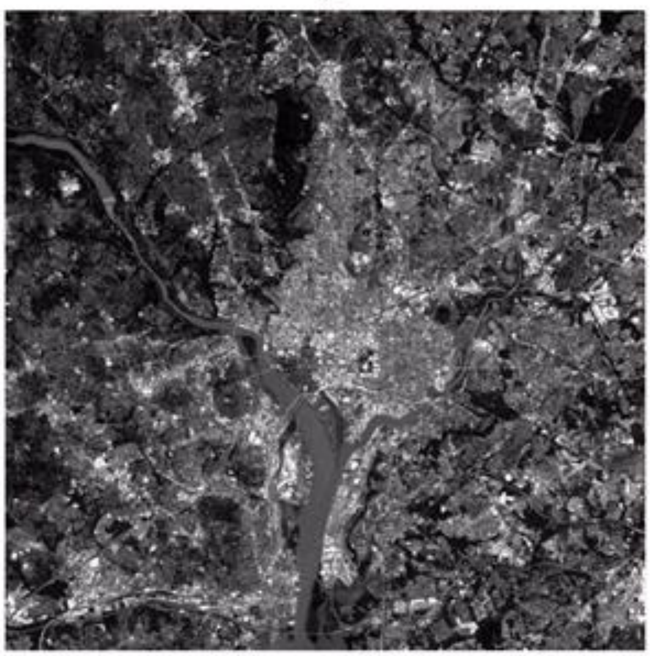


Figure 9.5 (a) Staircase Structure (b) Structure coded in terms of the primitives a and b to yield the string description... ababab..

(c)Tree description is more powerful than string ones. Most hierarchical ordering schemes lead to tree structure.



Satellite image of a heavily built downtown area (Washington, D.C.) and surrounding residential areas. (Courtesy of NASA.)

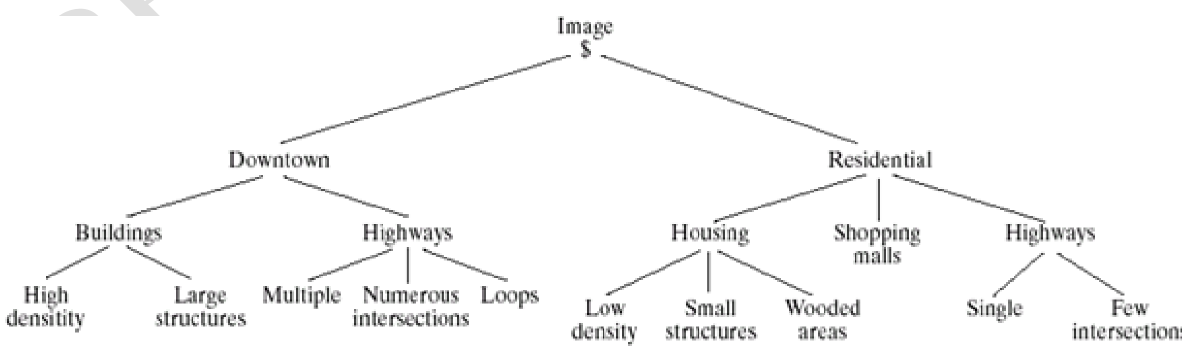


Figure 9.6 Tree Structure

9.2 Decision Theoretic Methods

- Decision-theoretic approaches to recognition are based on the use decision functions. Let $\mathbf{x} = (x_1, x_2, \ldots, x_n)^T$ represent an n-dimensional pattern vector. For W pattern classes $\omega_1, \omega_2, \ldots, \omega_W$, we want to find W decision functions $d_1(\mathbf{x}), d_2(\mathbf{x}), \ldots, d_W(\mathbf{x})$ with the property that, if a pattern x belongs to class ω_i, then $d_i(\mathbf{x}) > d_j(\mathbf{x}) \quad j = 1,2,\ldots,W;\ j \neq i$

- The decision boundary separating class ω_i and ω_j is given by

  $d_i(\mathbf{x}) = d_j(\mathbf{x})$ or $d_i(\mathbf{x}) - d_j(\mathbf{x}) = 0$

(a) Minimum Distance Classifier

- Suppose that we define the prototype of each pattern class to be the mean vector of the patterns of that class:

$$m_j = \frac{1}{N_j} \sum_{x \in w_j} x_j$$

j=1,2,…,W (1)

- Using the Euclidean distance to determine closeness reduces the problem to computing the distance measures

$$D_j(x) = \|x - m_j\|$$

j=1,2,…,W (2)

- The smallest distance is equivalent to evaluating the functions $d_j(x) = x^T m_j - \frac{1}{2} m_j^T m_j$

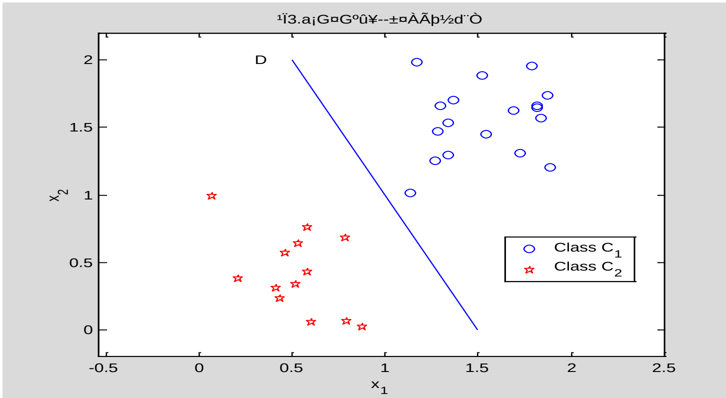
j=1,2,…,W (3)

- The decision boundary between classes and for a minimum distance classifier is

$$d_{ij}(x) = d_i(x) - d_j(x) \qquad = x^T(m_i - m_j) - \frac{1}{2}(m_i - m_j)^T(m_i + m_j) = 0$$

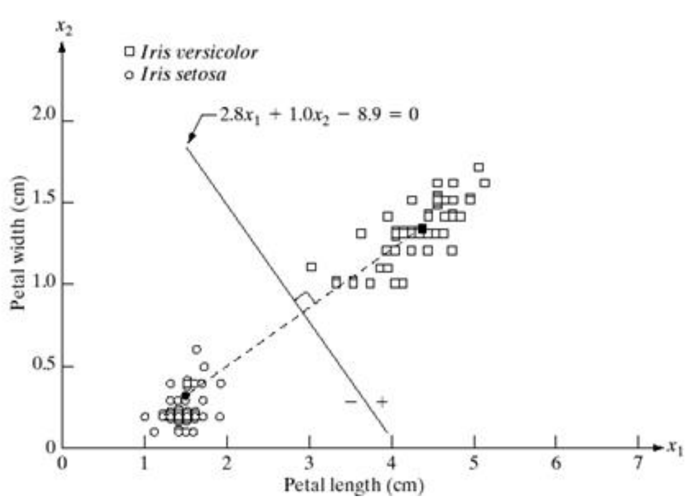
j=1,2,…,W (4)

- Decision boundary of minimum distance classifier



- Advantages:
    1. Unusual direct-viewing
    2. Can solve rotation the question
    3. Intensity
    4. Chooses the suitable characteristic, then solves mirror problem
    5. We may choose the color are one kind of characteristic, the color question then solve.
- Disadvantages:

1. It costs time for counting samples, but we must have a lot of samples for high accuracy, so it is more samples more accuracy.
2. Displacement
3. It is only two features, so that the accuracy is lower than other methods.
4. Scaling



Decision boundary of minimum distance classifier for the classes of *Iris versicolor* and *Iris setosa*. The dark dot and square are the means.

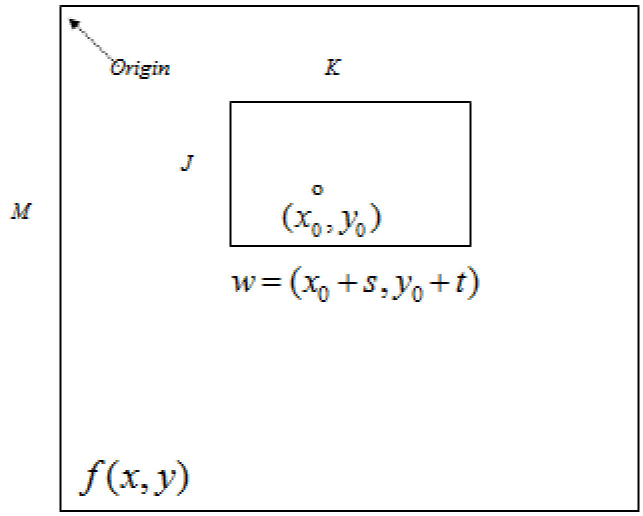
(b) Matching by Correlation

- We consider it as the basis for finding matches of a sub-image of size $J \times K$ within $f(x,y)$ an image of $M \times N$ size , where we assume that $J \le M$ and $K \le N$

$$c(x,y) = \sum_s \sum_t f(s,t)w(x+s,y+t)$$

for x=0,1,2,…,M-1,y=0,1,2,…,N-1 (5)

- Arrangement for obtaining the correlation of f and w at point (x_0, y_0)



- The correlation function has the disadvantage of being sensitive to changes in the amplitude of f and w .For example, doubling all values of f doubles the value of $c(x, y)$
- An approach frequently used to overcome this difficulty is to perform matching via the *correlation coefficient*

$$\gamma(x,y) = \frac{\sum_s \sum_t [f(s,t) - \bar{f}(s,t)][w(x+s, y+t) - \bar{w}]}{\left\{ \sum_s \sum_t [f(s,t) - \bar{f}(s,t)]^2 \sum_s \sum_t [w(x+s, y+t) - \bar{w}]^2 \right\}^{\frac{1}{2}}}$$

- The correlation coefficient is scaled in the range-1 to 1, independent of scale changes in the amplitude of f and w

Advantages:

1. Fast
2. Convenient
3. Displacement

Disadvantages:

1. Scaling

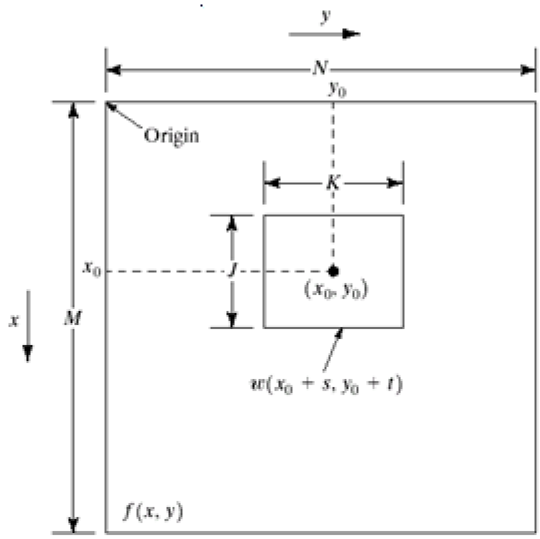
2. Rotation
3. Shape similarity
4. Intensity
5. Mirror problem
6. Color cannot recognition

- **The correlation between *f*(*x*,*y*) and *w*(*x*,*y*) is**

$$c(x, y) = \sum_s \sum_t f(s,t)w(x+s, y+t)$$

for $x = 0,1,2,\ldots, M-1,$

$y = 0,1,2,\ldots, N-1$



Arrangement for obtaining correlation of f and w at point (x_0,y_0)

(i) Statistical Supervised Classification

Optimum statistical classifiers (Bayes Classifier)

It is type of supervised classification on which the hypothetical or probability of that classification on which the hypothetical or probability of that classification is determined using presence of user signal or sample signal or teacher signal or target signal. This still can be extended to classification of features or pattern where similar type of patterns are grouped into one class that is same as the characteristics of user signal..

The term similar in containing objects is closeness to the features between sample signal and segmented region. To justify this classification we use Bayesian Classifier.

Bayesian Classifier

A Bayesian Classifier is simple probabilistic classifier Bayesian theorem. The Bayesian Classifier classified the features to contribute the probability of hypothetical evidence.

P(Hi/E)= P(E/Hi).P(Hi) $/ [\sum_{n=1}^{k} P\left(\frac{E}{Hn}\right).P(Hn)$

Where

P(E/Hi)=The probability that we will observe evidence "E" given that Hypothesis "Hi" is true

P(Hi)=A prior probability that the hypothesis Hi is true

P(Hi/E)=The probability that we will observe hypothesis "Hi" given that evidence "E" is true

K=The number of possible hypothesis

Bayes Classifier

The probability that a particular pattern **x** comes from class w_i is denoted $p(w_i/x)$

If the pattern classifier decides that **x** came from w_j when it actually came from w_i, it incurs a loss, denoted L_{ij}

$$r_j(x) = \sum_{k=1}^{W} L_{kj}\, p(w_k/x)$$

- From basic probability theory, we know that

$$p(A/B) = [p(A)p(B/A)]/p(B)$$

$$r_j(x) = \frac{1}{p(x)} \sum_{k=1}^{W} L_{kj}\, p(x/w_k)\, P(w_k)$$

$$r_j(x) = \sum_{k=1}^{W} L_{kj}\, p(x/w_k)\, P(w_k)$$

- Thus the Bayes classifier assigns an unknown pattern **x** to class w_i

$$\sum_{k=1}^{W} L_{ki}\, p(x/w_k)\, P(w_k) < \sum_{q=1}^{W} L_{qj}\, p(x/w_q)\, P(w_q)$$

$$L_{ij} = 1 - \delta_{ij}$$

$$r_j(x) = \sum_{k=1}^{W} (1-\delta_{kj})\, p(x/w_k)\, P(w_k)$$

$$= p(x) - p(x/w_j)\, p(w_j)$$

- The Bayes classifier then assigns a pattern x to class w_i if,

$$p(x) - p(x/w_i)P(w_i) < p(x) - p(x/w_j)P(w_j)$$

- or, equivalently, if $$p(x/w_i)P(w_i) > p(x/w_j)P(w_j)$$

$$d_j(x) = p(x/w_j)\,P(w_j)$$

- Bayes Classifier for Gaussian Pattern Classes
- Let us consider a 1-D problem (n=1) involving two pattern classes (W=2) governed by Gaussian densities

$$d_j(x) = p(x/w_j)\,P(w_j) \quad = \frac{1}{\sqrt{2\pi}\sigma_j} e^{-\frac{(x-m_j)^2}{2\sigma_j^2}} P(w_j)$$

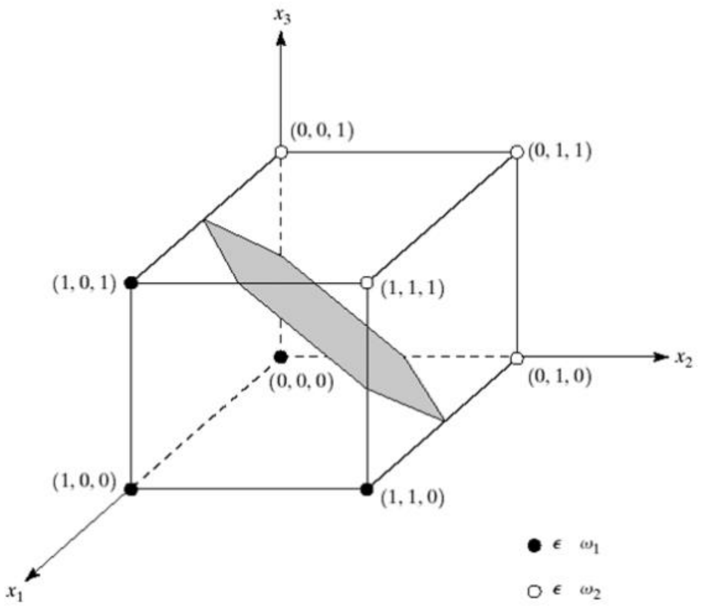
$$j = 1, 2$$

- In the *n*-dimensional case, the Gaussian density of the vectors in the *j*th pattern class has the form

$$p(x/w_j) = \frac{1}{(2\pi)^{n/2} \left|C_j\right|^{1/2}} e^{-\frac{1}{2}(x-m_j)^T C_j^{-1}(x-m_j)}$$

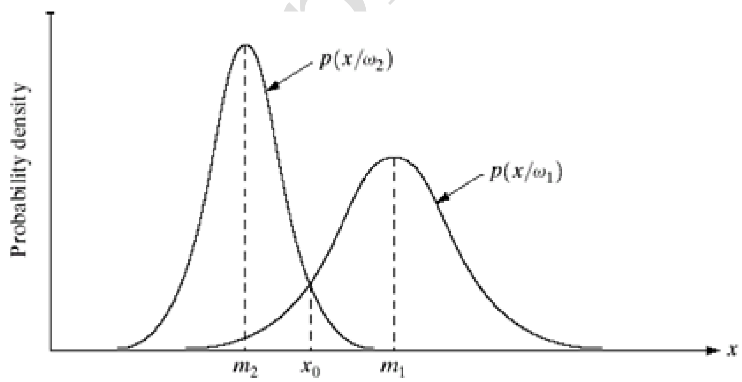
- Advantages:
  1. The way always combine with other methods, and then it got high accuracy
- Disadvantages:
  1. It costs time for counting samples
  2. It has to combine other methods

$$d_j(x) = p(x \mid \omega_j)\, p(\omega_j) = \frac{1}{\sqrt{2\pi}\sigma_j} e^{-\frac{(x-m_j)^2}{2\sigma_j^2}} p(\omega_j)$$



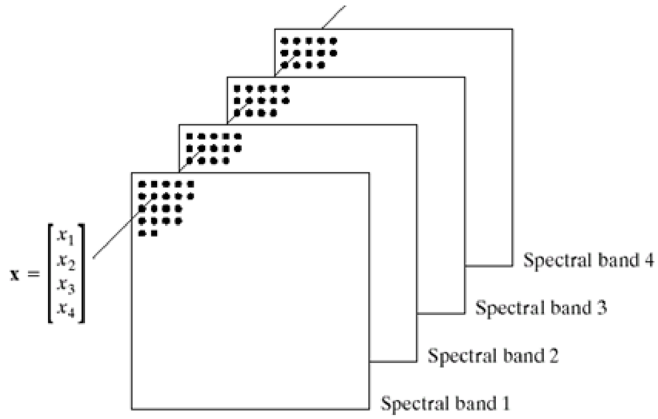
Two simple pattern classes and their Bayes decision boundary (shown shaded).

Probability density functions for two 1-D pattern classes. The point x_0 shown is the decision boundary if the two classes are equally likely to occur.



Classification of multi-spectral data using the Bayes classifier

Formation of a pattern vector from registered pixels of four digital images generated by a multispectral scanner.



(ii)Distribution Free

It is type of supervised classification and don't require knowledge of any density function on p.d.f based on the heuristic information or algorithm. The example of distribution free is Nearest Neighborhood Classification so that it is also called as Neighborhood Classification. Therefore it works as follows:

(1)We create a database of any object for which we already know that the correct classification should be known .When the system is given a query i.e. new object classify the system. It finds the nearest neighborhood of the query in the database.

(2) Then the system classify the query as belongs to the same classes as its nearest neighbors .i.e. Database image

1	**2**	**3**
2	**4**	**4**
5	**0**	**2**

→

1	**2**	**3**
2		
5	**0**	**2**

I/P Query "4"

Recognition digit using Neighborhood Classifier

(3) Then the system classifies the query as an image of 4.

(4) Now the image is identified and classify by the distribution free Supervised Classification. Here query

4 is the target signal by the user.

9.3 Overview of Neural Networks in Image Processing

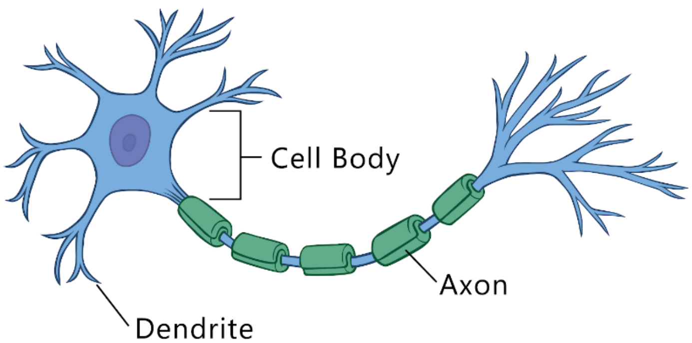


Figure 9.7 Neural Components

Neuron:

A neuron is a cell in the brain whose principle function is the collection, processing and dissemination of electrical signal. **The cell body** is a part of the cell containing nucleus and maintaining protein synthesis. A neuron may have many **dendrites** which branch out tree like structure and receive signals from other neurons. The **axon** conducts the electric signal generated at the axon hillock.

Neural Network (NN) and Artificial Network (ANN):

Neural Network is the branch of the field known as AI. A neural network can be considered as black-box i.e. able to prediction of output pattern when it recognizes the given input pattern. Artificial Neural Network (ANN) is the type of Neural Network which is inspired as artificially to show the human behavior. ANN shows the brain process information system.

Why use NN?

NN is only used for following:

(a) Self Organization

(b) Real Time Operations

(c) Information is distributed over the entire network.

(d) Adaptive Learning

Applications of Neural Networks (NN)

(i) Automotive, Automobile and Automatic Guidance System.

(ii) Aerospace and Aircraft component simulation.

(iii) Banking cheque reader

(iv)Different facial recognition

(v) Manufacturing Product Design (CAD)

(vi)Telecommunication automated information

(vii) Robotics Control System

Dis-Advantages of Neural Networks (NN)

(i) NN needs training to operate.

(ii) The architecture of NN is different from the architecture of micro-processor.

(iii) Requires high processing time for large neural network

(iv) Hard to setup programming.

(v) Lack of well manpower.

Applications of NN in Image Processing

(i) NN for Image Compression

(ii) NN for Pattern Recognition

(iii) NN for Perception (Perception)

(i) NN for Image Compression

NN model have received much attention in many fields where high compression ratio is required. Many NN approaches for image compression gives superior performance than the discrete traditional approach. Digital Image generated with 8-bit may be reduced in size by feeding it to. Neural Network (NN) on the other side then process the compressed image by 4X8 multilayer NN for reconstruction

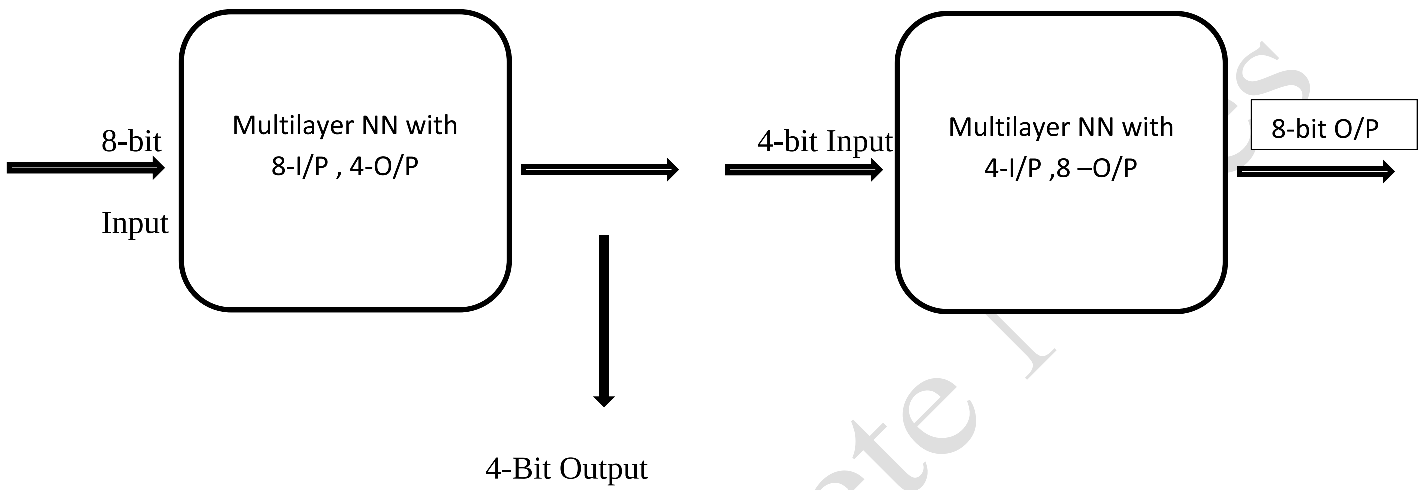


Figure 9.8 Basic Block Diagram of Image Compression

(ii) NN for Pattern Recognition

The NN is ideal tool for pattern recognition. Any recognition system needs to be trained to recognize different patterns. NN is also simplification of human neuron network system. It is more likely to adapt the human way of solving the recognition problem than other techniques. The design of NN system for Pattern Recognition starts from collecting data on each of objects that is to recognized by the system.

For Example:

A dealer has a warehouse that stores variety of fruits and vegetables that are mixed together. The dealer wants a machine that will sort the fruits according to their type. The fruit is loaded on the conveyer belt and the fruit passes through the sensor which measures the shape, texture ,color and weight properties.

The output will be input to the purpose of NN is to decide what kind of fruit is on the conveyer belt. So, fruits can be directed to the correct storer.

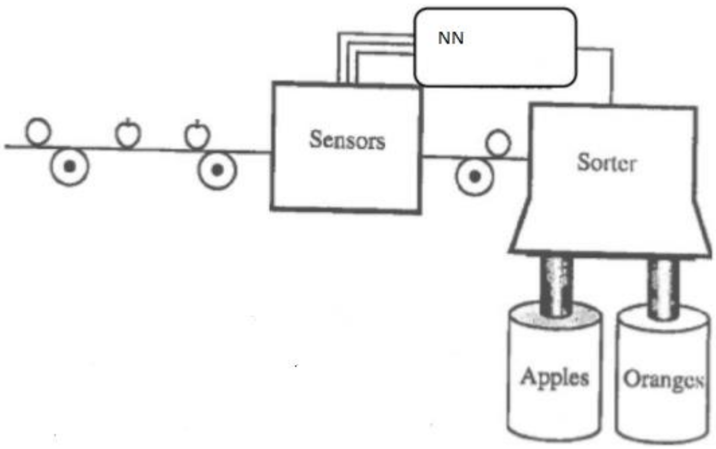


Figure 9.9 Block Diagram of Pattern Recognition

(iii) NN for Perceptron (Perception):

It is one of the earliest neural network model .Here i/ps from one or more previous neurons are individually weighted and then summed. The result is non-linearly scaled between 0 and +1.And then, the result is passed to the neurons in the next layer for output result.

Several perceptions can be combined to form multi-layer perception (MLP).So MLP is a development from the simple perception in which extra hidden layers are added. Here more than one layer can be used. Generally, connections are allowed from input layer, hidden layer and so on. At first i/p are feeded into the i/p layer and get multiplied by inter-connection weights as they are passed from i/p layer to the first hidden layer.

After first layer then go to the second layer and finally data is multiplied by inter-connection weight and so on. Back propagation never take the perception methods but at the time of sensing accuracy it is used.

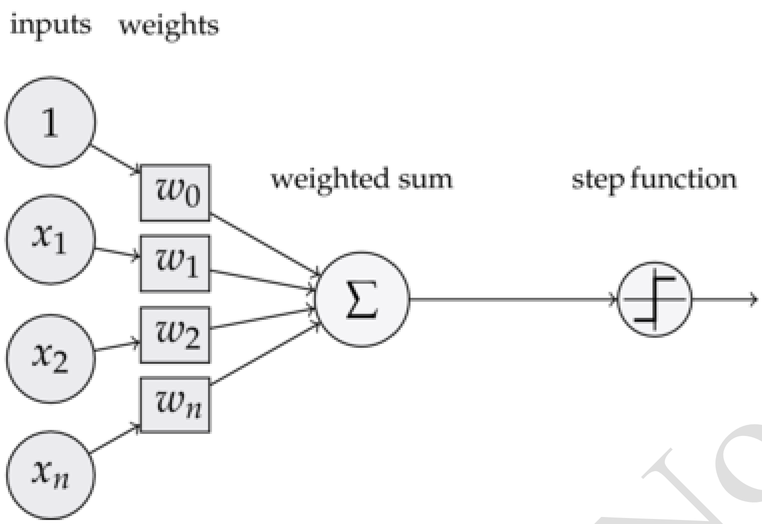


Figure 9.10: Block Diagram of Perceptron

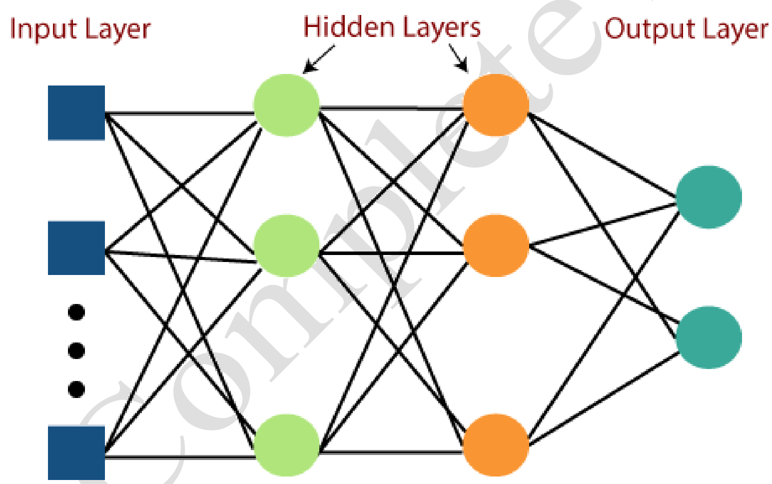


Figure 9.11: Formation of Output by Perceptron