Fundamental Concept of Digital Image Processing

Semester: I

Paper Code: GIS 04
Name of Paper: Digital Image Processing

PG Diploma in RS & GIS

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Fundamental Concept of Digital Image Processing

5.1 Flow of Digital Image Processing

Digital image processing is required for the following cases in GIS.

- Integration of remote sensing and GIS, particularly with satellite imagery of Landsat, SPOT, JERS-1, ERS-1, Radarsat, IRS etc.
- Automated digitization from rasterized map data using scanners
- Computer mapping with color output in raster format
- Visualization in three dimensional bird痴 eye view
- Editing of image database

Digital image processing includes the following procedures, as shown in Figure 5.1.

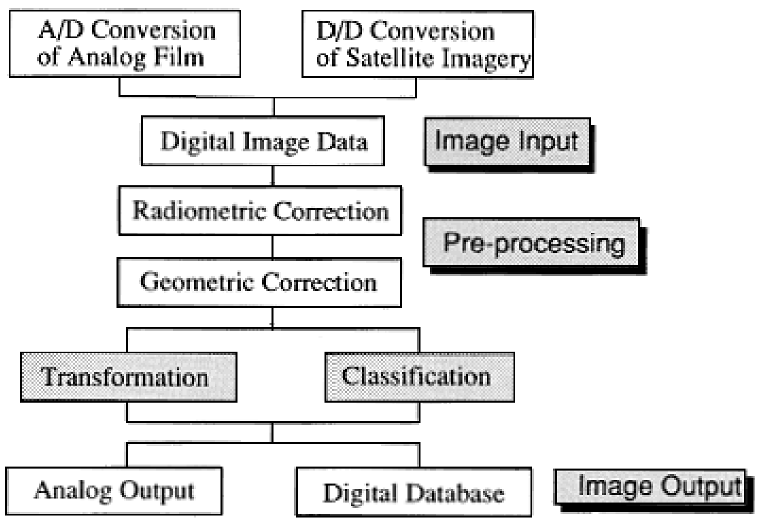


Figure 5.1 Flow of Digital Image Processing

Image input: to acquire digital image data by scanning analog films or maps. Satellite imagery is provided in computer compatible tape (CCT) or CD-ROM.

Preprocessing: two procedures of radiometric correction and geometric correction are required.

Image Transformation: two procedures of image enhancement and feature extraction will be implemented depending on the specific purposes as shown in Figure 5.2

Classification: thematic maps such as land cover/land use, soil, forest, geology etc. will be produced.

Image output: two products of analog image out put and digital image database will be the result of digital image processing.

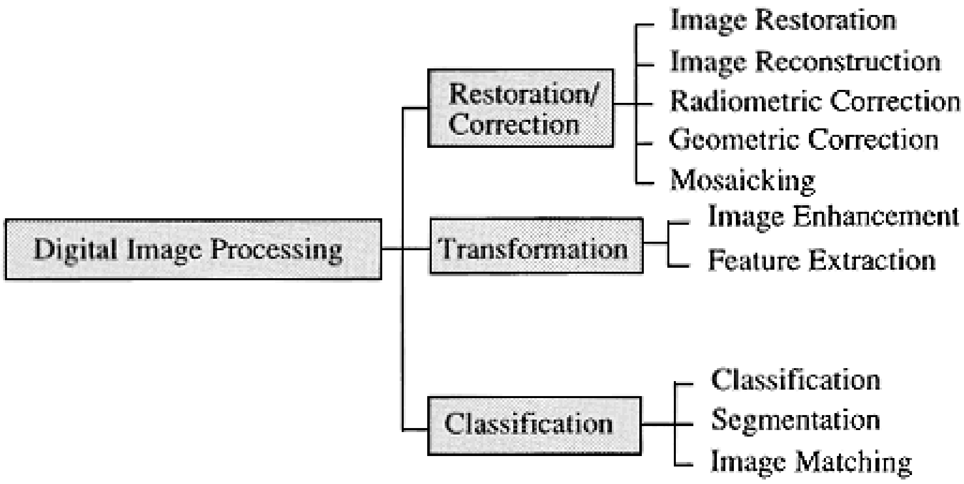


Figure 5.2 Major Procedures in Digital Image Processing

5.2 Radiometric Correction

Radiometric is a pre-processing technique to reconstruct physically calibrated values by correcting the spectral distortions caused by sensors, sun angle, topography and the atmosphere as shown in Figure 5.3. Radiometric correction is classified into two types; absolute and relative correction.

Absolute correction: Correct radiance or reflectance should be measured or converted by using the sensor calibration data, the sun angle and view angle, atmospheric models and ground truth data. The incident energy input to sensors as shown in Figure 5.4 should be analyzed correctively by radiometric correction. However it can not be applied in most applications, therefore the relative correction is applied because the atmospheric model is so complicated and the exact measurement of atmospheric condition is difficult.

Relative Correction: Relative correction is to normalize multi-temporal data taken on different dates to a selected reference data at specific time.

The following techniques will be typical.

- Adjustment of average and standard deviation values.
- Conversion to normalized index: for example the normalized difference vegetation index (NDVI).

$$NDVI = \frac{Infrared\ band - Red\ band}{Infrared\ band + Red\ band}$$

- Histogram matching: the histograms per band and/or per sensor are calculated and the cumulative histogram with cut-offs at 1% and 99% will be relatively adjusted to the reference histogram as shown in Figure 5.5.

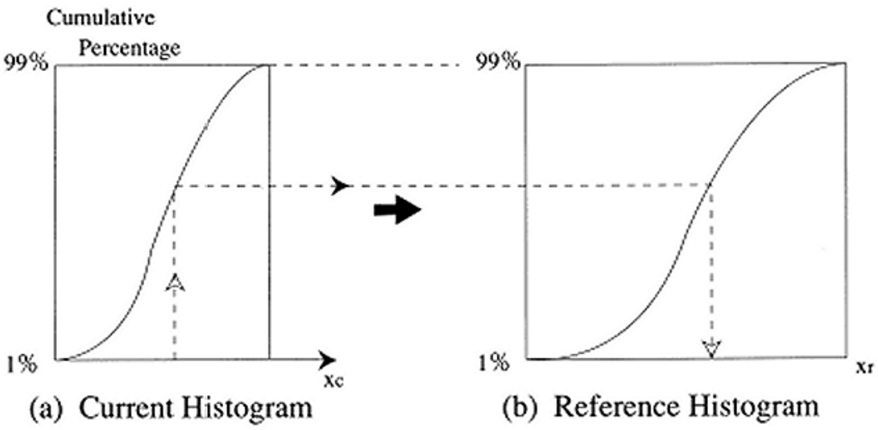


Figure 5.5 Histogram Matching

- Least square method: linear function of $y = ax + b$ is determined, where y is reference data and x is data to be normalized.

5-3 Geometric Correction

Geometric correction is to correct the geometric distortions; internal and external distortions as shown in Figure 5.6.

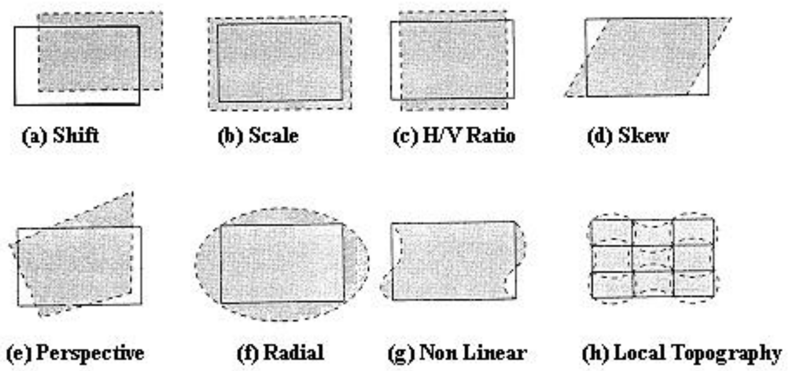


Figure 5.6 Various Types of Geometric Distortions

internal distortions: caused by sensor, such as lens distortion, misarrangement of detectors, variation of sampling rate etc.

external distortions: caused by external parameters other than sensor, including variation of attitude and position of platform, earth curvature, topographic relief etc.

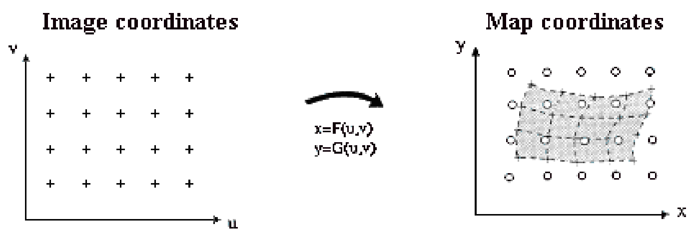
Geometric correction is made according to the following steps.

step 1: Data input of uncorrected image data
step 2: Selection of geometric correction method and transformation equation depending on the sensor geometry and the estimated types of geometric distortions
step 3: Determination of transformation parameters using ground control points (GCP)
step 4: Resampling and interpolation
step 5: Output georeference image, known as geo-coded image

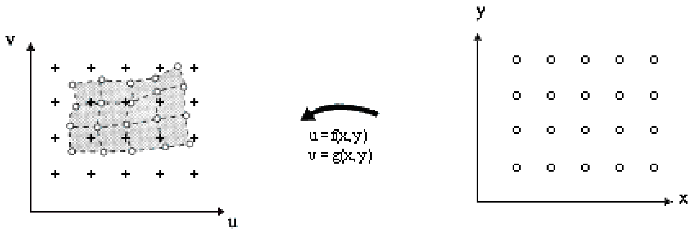
There are three types of geometric correction.

System correction: geometric correction using the geometry of the sensor with sensor calibration data and attitude/positioning measurements. But this is not enough to produce geo-coded image with high accuracy.

Mapping transformation: determination of transformation function, usually the second of third order polynomials to transform image to map coordinate system based only on ground control points (see Figure 5.7).



(a) Transformation of Image Coordinates onto Map Coordinate System



(b) Transformation of Map Coordinates onto Image Coordinates System

Figure 5.7 Transformation in Geometric Correction

Combined method: at the first stage, system correction is adopted to avoid major systematic distortions and then mapping transformation with simpler functions such as affine or pseudo-affine is applied with fewer number of GCPs.

5.4 Image Enhancement

Image enhancement is conversion of the original imagery to a better understandable level in spectral quality for feature extraction or image interpretation.

The following techniques are typical in image enhancement.

Gray scale conversion (see Figure 5.8.)

Contrast stretch (linear), fold conversion, saw conversion etc. are involved.

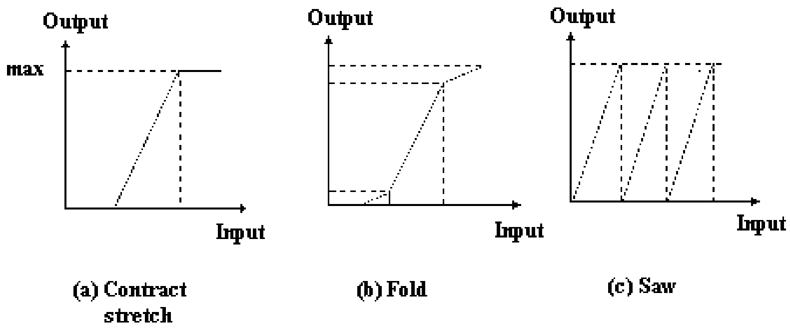


Figure 5.8 Grey Scale Conversion

Histogram conversion (see Figure 5.9.)

The histogram of the original image is converted to other types of histogram as specified by users. Histogram equalization with flat histogram or linear cumulative histogram and histogram normalization with normalized histogram are popular.

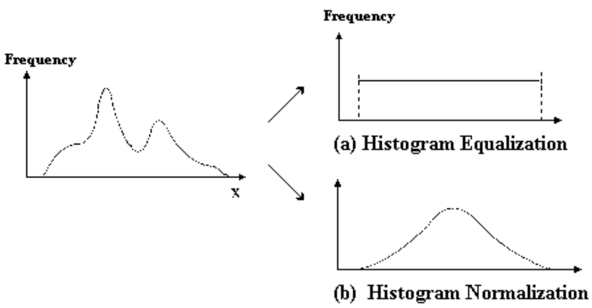


Figure 5.9 Histogram Conversion

Colour composition

Colour composition is the assignment of three primary colours; red (R), green (G) and blue (B) to three selected bands from multispectral bands usually available for satellite remote sensing image data. Table 5.1 shows several colour compositions and their characteristics. Colour composition is demonstrated in the front pages of this book.

Table 5.1 Typical Color Composition

Spectral Bands	Assignment of Primary Color	Color Output
(1, 2, 3)	(B, G, R)	Almost natural color
(2, 3, 4)	(B, R, G)	Pseudo natural color
(2, 3, 4)	(B, G, R)	"Color Infrared" with vegetation in red and water in dark blue
(2, 3, 4)	(R, G, B)	Turbid water in pink or purple

Remark: 1: Blue Band, 2: Green Band, 3: Red Band, 4: Near Infrared Band

Colour Conversion

Though R, G and B are primary colours with more convenience for computer processing, three colour elements of hue (H), intensity (I) and saturation (S) are more easily understood by human visual sense. Colour conversion between RGB and HIS colour system will be useful to obtain better colour quality or variety for interpretation. Multi-sensor fusion, for example, with optical multi-spectral bands and another sensor black and white image such as SAR (synthetic aperture radar) or high-resolution panchromatic band is implemented by replacing I (intensity) by B/W band after colour conversion from RGB (only with optical multi-bands) to HIS.

5.5 Spatial Filtering

Spatial filtering is commonly used for the following purposes.

- to restore imagery by avoiding noises
- to enhance the imagery for better interpretation
- to extract features such as edges and lineaments

There are two methods;

Filtering in the domain of image space

Generally local convolution with a window operator of *n ´ n* matrix is used. Table 5.2 shows several typical 3 x 3 window operators and their effects. Sobel, Laplacian and High pass filters are useful to detect or extract linear features and edges. Mean and Median filters are required to avoid high frequency noises, for example in the images of water surface with subtle tone change.

Filtering in the domain of spatial frequency

The Fourier transformation is conventionally used to convert from image space domain to spatial domain of which frequency is controlled by low pass, high pass and band pass filters. After such frequency domain filtering, image will be reconstructed by using an inverse Fourier transformation.

Low pass filters will cut off high frequency to allow the output of only low frequency image, while high pass filters will cut off low frequency noises such as stripe noise or shading.

Table 5.2 Major Spatial Filters

Filters	3×3 Window Operator	Effects
Mean	$A=\frac{1}{9}\begin{bmatrix}1&1&1\\1&1&1\\1&1&1\end{bmatrix}$ or $\frac{1}{5}\begin{bmatrix}0&1&0\\1&1&1\\0&1&0\end{bmatrix}$	smoothing without noises but with loss of sharpness
Sobel	$A_x=\begin{bmatrix}-1&0&1\\-2&0&2\\-1&0&1\end{bmatrix}$, $A_y=\begin{bmatrix}1&2&1\\0&0&0\\-1&-2&-1\end{bmatrix}$ $\lvert A_x\rvert+\lvert A_y\rvert$ or $\sqrt{A_x^2+A_y^2}$	gradient and linear features are enhanced
Laplacian	$A=\begin{bmatrix}0&-1&0\\-1&4&-1\\0&-1&0\end{bmatrix}$ or $\begin{bmatrix}-1&-1&-1\\-1&8&-1\\-1&-1&-1\end{bmatrix}$	differential and linear features are enhanced
Median	Replaced by the median value of 3×3 window	smoothed image with a little loss of sharpness
Highpass	$A=\begin{bmatrix}0&-1&0\\-1&5&-1\\0&-1&0\end{bmatrix}$ or $\frac{1}{9}\begin{bmatrix}-1&-1&-1\\-1&8&-1\\-1&-1&-1\end{bmatrix}$	edge enhancement
Sharpening	$A=\frac{1}{9}\begin{bmatrix}1&-8&1\\-8&37&-8\\1&-8&1\end{bmatrix}$	sharpened with clearness

As the Fourier transformation will not be able to localize the frequency domain filtering, the Wavelet function has become more useful to detect particularly edges, because it enables to select an optimum window size locally.

Examples of images applied by various filters are shown in the front pages of this book

5.6 Feature Extraction

Feature extraction is the operation to extract various image features for identifying or interpreting meaningful physical objects from images.

Features are classified into three types.

Spectral features: colour, tone, ratio, spectral index etc. Principle components and normalized vegetation index are widely used.

The first and second principle components computed from satellite multi-spectral scanner data such as Landsat TM will give "brightness" and "greenness" respectively.

Normalized difference vegetation index (NDVI) is often used for vegetation classification.

$$NDVI = \frac{Infrared - Red}{Infrared + Red}$$

Geometric features: edges, lineaments etc.
Spatial filtering of edge detection is commonly used to extract linear features such as roads, geological lineaments, boundaries of agricultural fields etc.

Generally spatial filtering is applied as follows.

Step 1: smoothing filter such as mean or median is applied to avoid high frequency noises.
Step 2: edge detection filter such as Sobel, Laplacian or High pass is applied to detect edges.
Step 3: line edges are detected by thinning and sometimes edge closing.

Textural features: pattern, homogeneity, spatial frequency, etc.
Though many computer approaches have been tried, human pattern recognition is much better than the computer results.

Table 5.3 summarizes major operations of feature extraction

Table 5.3 Major Operations of Feature Extraction

Feature Type	Operation	Extracted Feature
Spectral Features	Principal Component Analysis	· Color composition with PC1, PC2 and PC3 will give more colorful image output · PC1 : brightness · PC2 : greenness
	Normalized Difference Vegetation Index (NDVI)	· High value corresponds to higher vegetation density · Forest, grassland bare soil and water are easily delineated by NDVI
Geometric Features	Spatial Filtering	· Edges are detected for identifying roads, lineaments, building etc.
	Stereo-matching	· 3D coordinates of terrain points are computed for DEM · 3D lines are identified from edges
Textural Features	Statistical Operations	· Homogeneous areas are recognized · Coarse patterns with peaks are detected
	Fourier Transformation	· Repeated patterns and orientation are recognized

5.7 Classification Methods

Computer assisted classification of multispectral imagery in remote sensing is useful for thematic mapping of land use, vegetation, soil, geology etc.

Classification methods are classified into two categories.

Supervised classification: classification with the use of ground truth data in the form of sample sets. Maximum likelihood classifier is one of the typical supervised classification methods.

Unsupervised classification: classification with only spectral features without use of ground truth data. Clustering is an unsupervised classification in which a group of the spectral values will regrouped into a few clusters with spectral similarity.

The following classification methods are widely used depending on the spectral characteristics and availability of ground truth data as shown in Figure 5.10.

Rationing: classification between vegetation and non-vegetation is possible.

Box classifier: very easy to apply level slicing but accuracy is not very high.

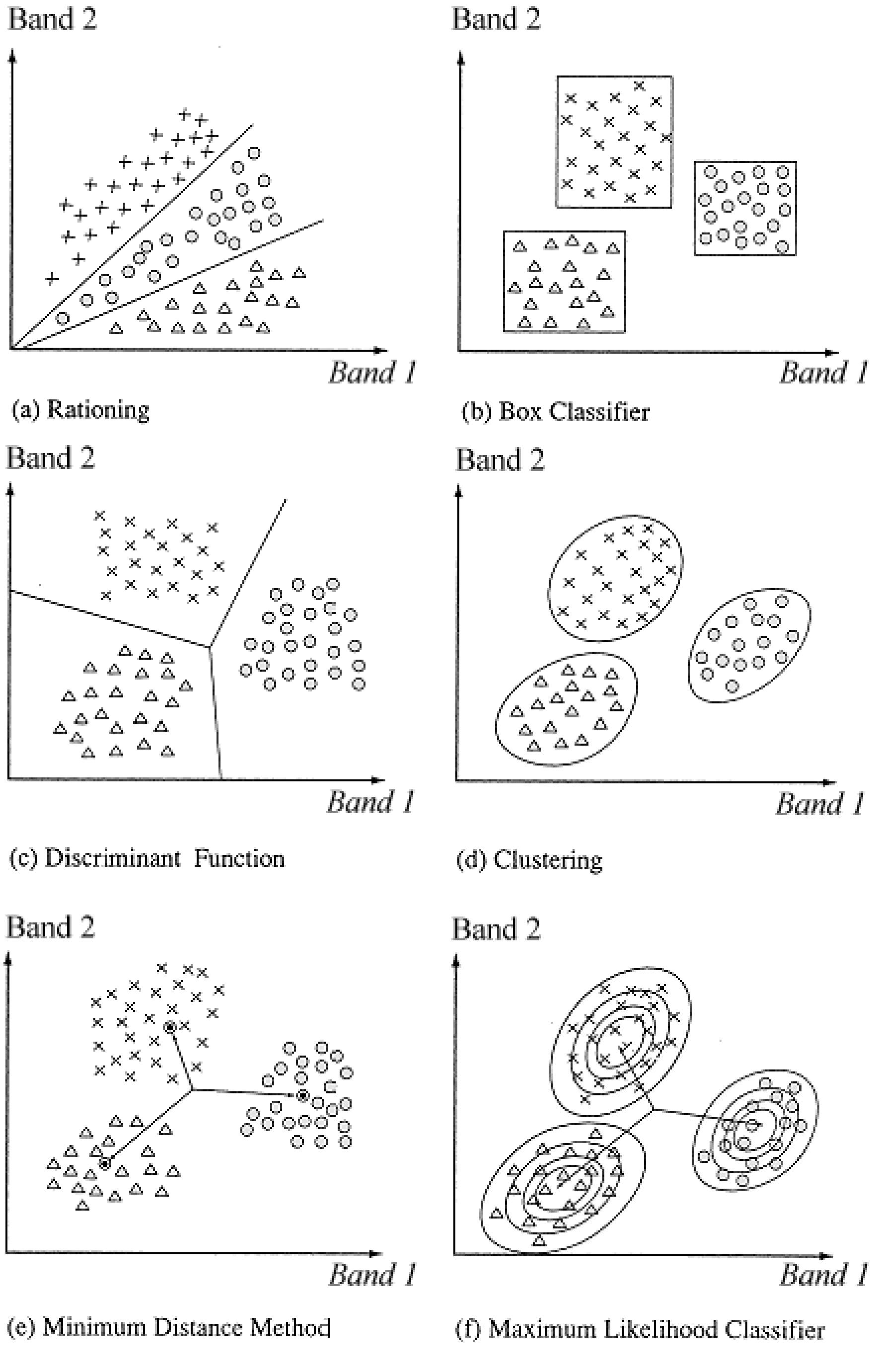


Figure 5.10 Typical Classification Method

Discriminant function: useful in the case when the number of classes is not many.

Clustering: unsupervised classifier with spectral similarity or distance between clusters.

Minimum distance method: several statistical distance measures such as Euclidan, Mahalanobis, Bhattacharya and Jefrey-Matsushita distance are used to determine the class.

Maximum likelihood classifier:

Knowledge-based classification including decision tree classifier will be specified as classification model by users.

5-8 Maximum Likelihood Classifier

Maximum likelihood classifier is one of the most popular methods for thematic mapping with satellite multispectral imagery.

An unknown pixel ***X*** with multispectral values (n bands) will be classified into the class (*k*) that has the maximum likelihood

{ max L*k* (***X***) }.

The likelihood function is given as follows on the assumption that the ground truth data of class *k* will form the Gaussian (normal) distribution (see Figure 5.11).

$$L_k(\mathbf{X}) = \frac{1}{(2\pi)^{n/2}|\mathbf{S}_k|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{X}-\overline{\mathbf{X}}_k)^t S_k^{-1}(\mathbf{X}-\overline{\mathbf{X}}_k)\right\}$$

$$\mathbf{X} = \begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{pmatrix} : \textit{image data of bands}$$

where:

$\overline{X}_k$: mean vector of the ground truth data in class *k*

S_k : Variance-covariance matrix of K class produced from the ground truth data

$|S_k|$: determinant of ***S****k*

For practical computation, the above likelihood is converted to the discriminant function in the form of logarithm.

*Gk (**X**) = In |**S**k| + d2k*

where *: d2k* = $(\mathbf{X} - \overline{\mathbf{X}}_k)^t S_k^{-1} (\mathbf{X} - \overline{\mathbf{X}}_k)$

Instead of maximum L*k* (***X***), class *k* that makes G*k* (***X***) minimum is searched for among the classes.

The maximum likelihood classifier is popular because of its robustness and simplicity. But there will be some errors in the results if the number of sample data is not sufficient, the distributions of the population does not follow the Gaussian distribution and/or the classes have much overlap in their distribution resulting in poor Separability.