Chapter 1

Prologue

1.1 Preamble

Agriculture plays an important role in economy of any nation. Economy of agricultural industries directly depends on the production of agriculture. A stable agricultural industry ensures a country of food security, source of income and source of employment. Agriculture production is an outcome of a complex interaction of soil, seed, water and agrochemicals. Enhancement of productivity needs proper type, quantity and timely application of soil, seed, water and agrochemicals at specific sites. This demands precision agriculture practices such as soil mapping, disease mapping at both seedling and plant level, weed mapping, selective harvesting and quality analysis of agricultural products (Grading of agricultural products).

Continuous assessment of these precision agriculture practices requires skilled labors. The availability of skilled labors is very short in most of agro-based developing countries and also it is certain that in a continuous process human cannot fulfill the above requirements precisely and accurately. The variations occurring in crop or soil properties within a field should be mapped and timely action need to be taken. But, humans are not consistent and precise in recording of spatial variability and its mapping. Hence, assessment may vary from an expert to an expert. This may lead to wrong assessment and it results in a poor quality of agricultural products. Therefore this demands automation of assessment of precision agriculture practices.
Since there is a requirement of precise and accurate assessment of precision agriculture practices, researchers have proposed intelligent models based on computer vision (CV) techniques to automate these practices for various commercial crops. The advantages of a computer vision based approach are that the accuracy is comparable to that of human experts and reduction of man power and time. Therefore, devising effective and efficient computer vision models to practice precision agriculture system for real time is the current requirement.

In this thesis, we have proposed segmentation and classification algorithmic models for precision agriculture practices such as disease mapping at seedling level, selective harvesting and grading. We have taken the tobacco crop as a case study to build these models. Due to the non availability of a large benchmark dataset on the tobacco crop, we have created our own large dataset for different stages of precision agriculture of tobacco crop. Extensive experiments are conducted on our own large dataset to show the efficacy of the proposed models.

The remaining part of this chapter is organized as follows. An overview of precision agriculture is presented and a case study of tobacco crop is given. A brief survey on existing related works on precision agriculture using computer vision is presented. Subsequently, objectives for the current work are presented. Thereafter, the measures which are generally used for evaluation of segmentation and classification models are presented. Finally, organization of the entire thesis is presented.

1.2 Precision Agriculture: An Overview

Precision agriculture is an integrated crop management system that attempts to match the type and quantity of inputs required for small areas within a farm field for a particular crop. The potential of precision agriculture in terms of economical and environmental benefits could be visualized through reduced use of water, fertilizers, herbicides and pesticides besides the farm equipments. Instead of managing an entire field based upon some hypothetical average condition, which may not exist anywhere in the field, a
precision agriculture approach recognizes site-specific differences within a field and adjusts management actions accordingly (Goovaerts, 2000). The objectives of precision agriculture are profit maximization, agriculture input rationalization and environmental damage reduction, by adjusting the agriculture practices to the site demands. To achieve these objectives some practices which are identification of diseases at seedling (nursery) level and plant level for site specific application of agrochemicals to remove diseases, selective harvesting of crops and grading (quality inspection) of crops are to be adopted. Human intervention in these practices raises many disadvantages such as wrong diagnosis of diseases in crops, wrong analysis of maturity of crops and wrong analysis of quality of crops. Therefore, we need to automate these practices to increase efficiency and speed using algorithmic models specifically image processing and pattern recognition techniques. The stages involved in a general precision agriculture system are shown in Figure 1.1.

![Block diagram of a general precision agriculture system](image)

Figure 1.1. Block diagram of a general precision agriculture system
1.2.1 Soil to Crop Mapping

Soil to crop mapping is being widely adopted in precision agriculture, as an initial step to identify soil variations (Mandal and Ghosh, 2000). Crop factors such as growth, quality and yield are mainly dependent on type of the soil. Soil properties that affect these factors include texture, structure, moisture, organic matter, nutrient status and landscape position (Adamchuk et al., 2004). Before farming any crop, the first task is to check if the soil is suitable for the particular crop or not. But, sometimes we may find the variations in soil properties within a single farm field. Therefore we need to map these areas. These maps will measure spatial variability along with the basis for controlling spatial variability. Visual properties of soil could be exploited to detect soil type and its properties using image processing and pattern recognition techniques. Remote sensing image data have been used in literature for soil sampling and mapping.

1.2.2 Disease Mapping

There is a tremendous pressure to reduce the usage of pesticides and fungicides in modern crop production to decrease the environment impact of current practices and to lower the production costs. Therefore, it is essential that sprays should be applied to affected areas (Lucas et al., 2001). Since lesion (infected) areas can occur on leaves, stem and seeds of the plant in an isolated and non-uniform fashion, sprays may get applied to healthy areas also. Therefore, disease control will be more efficient if lesion areas are identified and sprays are applied only to those lesion areas. This demands mapping of lesion areas across crop field. This in turn requires detection of lesion areas and diagnosing lesion area to decide the type of disease. Visual properties of diseases such as color, texture and shape could be exploited to identify lesion areas and diagnose the type of the disease using computer vision algorithmic models.

1.2.3 Weed Mapping

Weed mapping is one of the important practices of the precision agriculture. It minimizes the volume of herbicide by the use of site-specific weed management systems. This
avoids the application of herbicides to the crop. To do this, weed management system should segment weed patches from the crop field. Visual properties such as spectral signatures, shapes and textures could be exploited to segment weed patches using computer vision based weed management systems (Tellaeche et al., 2008).

1.2.4 Selective Harvesting

Harvesting is an important stage in any crop production. Selective harvesting is required for quality production. Selective harvesting is to collect only ripe crops from the field (Manickavasagam et al., 2007). Therefore, before harvesting a crop, farmers should look into factors such as unripe, ripe and over-ripe of crops. Judgment of crop ripeness by human will not always be accurate and precise due to human sensory limitation, variable lighting condition and loosing efficiency in evaluating crop ripeness over the time. Therefore there is a need to develop robust model against ecological conditions (sunny, cloudy and rainy) to evaluate ripeness of crop. Visual properties of crop such as color, texture and shape could be exploited to evaluate the ripeness of crop for harvesting purpose using computer vision algorithmic models.

1.2.5 Grading

Grading is the process of classification of crop products according to standards prescribed for the purpose. Grading is more important than the adoption of improved cultivation practices for high productivity (Manickavasagam et al., 2007). Grading scores will be used to measure the quality of crop products. It also makes pricing mechanism more simple, precise and meaningful. In the process of marketing, grading saves time and energy for both seller and buyer.

1.3 Case Study of Tobacco crop

Tobacco is a commercial crop across globe including India because of its high economic value. Especially in Karnataka, that too around Mysore district, many farmers are depending on tobacco crop because of the suitable climate condition and soil. It created a
gainful employment to several lakhs of people in India. Roughly 80% of the flue cured variety (FCV) of tobacco grown in Karnataka will be exported abroad to meet the demand of multinational cigarette manufacturing companies. According to statistics, in India during 2004-2005, revenue of about rupees seven thousand crores and a foreign exchange of about rupees fifteen hundred crores were generated from the tobacco crop. Although tobacco is largely used in cigarette industries, in recent years the alternative usage of tobacco is increased. In the year 2007, CTRI (Central Tobacco Research Institute) based in Guntur in Andrapradesh has bagged a patent right for “solansole”, a medicine extracted from tobacco, used in the manufacture of anti-cancer, anti-ulcer and cardiac drugs. Tobacco is an important medicine also in homeopathy for various minor ailments, such as dizziness, motion, sickness, diarrhea and dry cough, as well as numerous serious conditions, such as angina, cancer, chronic respiratory ailments and meniere’s disease. In addition, it is also used in cosmetic industries.

The emergence and spreading of diseases have become more common in tobacco at nursery (seedling) stage and plant stage, because of climate and environmental factors (Shenoi et al., 2006). These diseases are classified into two groups viz., nursery (seedling level) level diseases and field crop (plant stage crop) diseases. The diseases occurred in seedling level are anthracnose, soreshin and damping-off. The diseases occurred in field crop are brown spot, fusarium wilt, tobacco mosaic, leaf-curl, tobacco aphid and sooty mold. The diseases occurred in both seedling level and plant level are frog-eye spots, leaf blight, black shank, root-knot and stem borer.

In practice, the naked eye based observation method is mainly adopted in identifying and measuring the severity of diseases in seedlings level and plant level. The detection and measurement of severity of a disease vary from expert to expert due to difference of personal knowledge and practical experience. We need to spray agrochemicals into affected areas based on the severity of disease to reduce environmental pollution. Therefore, we need to develop computer vision algorithms to increase the speed and accuracy to detect, diagnose and measure the severity of disease so that one can spray site
specific application of specific pesticides and fungicides. This necessitates the
development of disease mapping system as a part of precision agriculture system of
tobacco crop (Figure 1.2).

While harvesting, farmers should look into a factor such as maturity (ripeness) of tobacco
leaves (i.e., right time harvesting) (Manickavasagam et al., 2007). Since the harvesting
work is concentrated in short time period, labor shortage tends to limit the farm acreage.
Hence, there is a possibility of harvesting of unripe tobacco leaves by human labors. This
will lead to low quality tobacco products. Over-ripe tobacco leaves are also leads to low
quality tobacco products. The computer vision techniques could be exploited for
classification of tobacco leaves for harvesting purpose, which increases the speed and
classification accuracy of harvesting and, reduces number of human labors. This demands
a development of selective harvesting system as a part of precision agriculture system of
tobacco crop (Figure 1.2).

There are six types of tobacco leaves such as flue cured virginia (FCV), cigar, burley,
pipe, chewing and snuff (Manickavasagam et al., 2007). Among these FCV tobacco
leaves are used for cigarette industries. India is one of the major producers of FCV
tobacco leaves. Once harvested, the tobacco must be cured without delay in order to start
stabilization of the material. There are four main curing processes: flue curing, fire
curing, air curing and sun curing. Among these, flue-curing process is used for FCV
tobacco leaves. The goal is to fix the color on yellow to get bright tobaccos. The flue-
curing consists of heating the air in a very well closed barn. An outside fire blows hot air
(very hot) into metal pipes running into the barn. There is no direct contact between the
fire and the tobacco, the hot pipes just heat the inside air.

Farmers do grading based on the quality of the flue-cured tobacco leaves before taking
them into a market. Quality inspection of the flue-cured tobacco leaves plays a crucial
role in quality assurance, since the quality of the flue-cured tobacco leaves determines the
quality of tobacco products. The quality inspection of cured tobacco leaves consists of
two main aspects – internal and external examinations (Zhang et al., 1997). The internal
quality inspection is usually achieved through chemical analysis, while the external quality inspection is mainly achieved through human vision. It is costly and yet time-consuming to inspect internal quality on a frequent basis since tobacco leaves contain too many ingredients to be handled at ease. As an alternative, external quality examination is often used instead of internal quality examination of tobacco leaves and also that the external features are closely related to internal features. The external quality inspection of cured tobacco leaves includes judgment of color, maturity, surface texture, size and shape. Human vision, which is inevitably limited by personal, physical and environmental factors, has been the predominant means of inspection. Especially tobacco grading requires more number of labors and consumes more time. Since tobacco has many grades, there is high probability of miss grading. Therefore, computer vision algorithms are needed to automate grading of cured tobacco leaves to achieve grading accuracy and speed. This requires the development of grading system as a part of precision agriculture system of tobacco crop (Figure 1.2).

![Block diagram of a precision agriculture system for tobacco crop](image)

Figure 1.2. Block diagram of a precision agriculture system for tobacco crop
1.4 Related Works

In this section, we provide a brief review on existing works related to disease mapping, selective harvesting and grading.

1.4.1 Models for Disease Mapping

Disease mapping involves two stages – identification (segmentation) of lesion areas and diagnosis (classification) of disease type. Wrong diagnosis of diseases on agricultural crops would damage the production and quality of crops. Therefore, it requires accurate segmentation and classification of lesion areas on crops. The challenges involved in building a disease mapping system using CV techniques are dataset creation of disease samples at variable lighting condition, segmentation of lesion areas at variable lighting condition, intra class variations and inter class overlapping. Tuning parameters of segmentation algorithm versus segmentation performance measures (see section 1.6) is also a challenging task.

Many attempts have been made on segmentation and classification of diseases in commercial crops such as mushrooms, maize, cotton, soyabean, citrus and cucumber. Enhancing color differences in images of mushrooms by means of vectorial normalization (Vizhanyo et al., 2000) was proposed to better separation of diseases. It was developed on the basis of statistical analysis of the distribution of color points. Conversion of a RGB image into H, I3a, and I3b color transformations and segmenting the transformed image by analyzing the distribution of intensities in a histogram (Camargo et al., 2009) was explored to identify plant disease visual symptoms. Color co-occurrence method (CCM) (Pydipati et al., 2006) was used in conjunction with statistical classification algorithms to identify diseased and normal citrus leaves under laboratory conditions. An algorithm to classify fall armyworm damaged maize plants and an undamaged maize plant at simplified lighting conditions (Sena et al., 2003) has also been recommended. A back propagation neural network (BPNN) and a gray level co-occurrence matrix (GLCM) (Huang, 2007) were used to evaluate the texture features of
the lesion area in seedling diseases. Fuzzy feature selection techniques are proposed for identifying diseases on cotton leaves. A subset of independent significant features (Zhang et al., 2007) was identified by exploiting fuzzy feature selection to get the best information for diagnosing and identifying diseases on cotton leaves. Grading method of leaf spot disease on soya bean leaf using image processing techniques was proposed. Leaf region (Weizheng et al., 2008) was segmented using Otsu method and disease spot regions were segmented using Sobel operator to trace disease spot edges. A method of recognizing disease in a cucumber leaf based on image processing and support vector machine (Youwen et al., 2008) was developed. Digital image analysis and spectral reflectance data (Mirik et al., 2006) are used to quantify damage by greenbugs in wheat crop. Severity of fungal disease in a spring wheat crop (Muhammed et al., 2005) was estimated using hyperspectral crop reflectance data vectors and corresponding disease severity field assessments. A method of using wavelet transform (Zhou et al., 2008) was developed to detect pests in stored grains. An image processing algorithm was proposed for automatic identification of whiteflies, aphids and thrips in greenhouse. The size and color components (Cho et al., 2007) were selected as features for automatic identification. Image processing, learning and knowledge based techniques (Boissard et al., 2008) were exploited for early pest detection in greenhouse crops. An adaptive approach for the identification of diseases in apple fruits (Dubey and Jalal, 2012) was proposed based on K-means clustering technique and multi-class support vector machine. They have tested the proposed model for three types of diseases on dataset of apple fruits.

From the above literature survey, we have understood that no attempt has been made on tobacco crop with respect to diagnosis of diseases at seedling level. Hence, there is a need of investigation and design of suitable segmentation algorithms and classifiers.

1.4.2 Models for Selective Harvesting

Few attempts could be traced on ripeness evaluation of crops for automatic harvesting. Direct color mapping method (Lee et al., 2011) was proposed for maturity evaluation of tomato and date fruits. A robotic system for harvesting ripe tomatoes in greenhouse (Yin
et al., 2009) was designed based on the color feature of tomatoes and morphological operations are used to denoise and handle the situations of tomato overlapping and shelter. Color quantization and image analysis technique in evaluating fruit maturity (Lee et al., 2008(a)) is demonstrated using Medjool date samples collected from field testing.

A novel and robust color space conversion and color index distribution analysis technique for automated date maturity evaluation (Lee et al., 2008(b)) was proposed. Computer vision technology for detecting fruit size, color, bruise, surface defects and evaluation of fruit overall quality (Gao et al., 2010) were discussed. A genetic algorithm based neural network detecting system (Xu, 2009) was developed for evaluating maturity of strawberry fruits. An intelligent and robust algorithm (Furfaro et al., 2007) operated on the multispectral images to estimate absolute percentages of under-ripe (green), ripe (yellow), and over-ripe (brown) coffee cherries displayed on the canopy surface. Feasibility of monitoring coffee field ripeness with airborne multispectral imagery (Johnson et al., 2004) was proposed. A Bayesian classifier considering a multivariate, three-class problem (Baltazar et al., 2008) was incorporated for data fusion to classify fresh intact tomatoes based on their ripening stages.

From the literature survey we have understood that no attempt has been made on harvesting of tobacco leaves using CV techniques. Therefore, we need to investigate suitable features to represent and also classifiers to classify tobacco leaves into unripe, ripe and over-ripe for harvesting purpose.

### 1.4.3 Models for Grading

A very few attempts have been made on grading of crops. Timmermans and Hulzebosch (1996) proposed a flexible grading system for pot plants. Experiments are conducted for classification of a flowered plant and a cactus plant. Neto et al., (2006) exploited elliptic fourier (EF) and discriminant analysis to identify young soyabean, sunflower, redroot pigweed and velvet leaf plants based on leaf shape. Principal component analysis was used to select the fourier coefficients with the best discriminatory power. Canonical discriminant analysis was used to develop species identification models. Liming et al.,
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(2009) devised a strawberry grading system based on three characteristics: shape, size and color. Multi-attribute decision making theory was adopted in this system. Chen et al., (2009) built a two stage classifier combining distance discriminant and a back propagation neural network (BPNN) to identify China corn varieties. A total of 17 geometric features, 13 shape features and 28 color features were extracted from color images of corn kernels.

A few attempts have been made especially on grading of flue-cured tobacco leaves. Zhang et al., (1997) proposed a grading system for cured tobacco leaves. A 2-D feature space to express feature distribution of cured tobacco leaves and nearest-neighbor method was used to classify cured tobacco leaves. The work is demonstrated on a very small dataset of 110 samples and considered 23 grades. The system has achieved an accuracy of about 64%. Zhang et al., (1998) presented a RGB to the Munsell transformation technique for color analysis of cured tobacco leaves. They have extracted munsell color features such as average hue and average chroma. Zhang et al., 2003 proposed a fuzzy classification system to grade cured tobacco leaves. Han (2008) applied fuzzy statistics and comprehensive judge techniques for recognition of the part of growth of flue-cured tobacco leaves based on support vector machine. He has considered only super-groups. Huabo et al., (2009) employed barrel theory decision-making algorithm to grade cured tobacco leaves. They have also considered super-groups and worked on very small dataset of 40 samples of four grades.

From the literature survey, we have understood that classification accuracy in grading of flue-cured tobacco leaves is less due to intra class variation and inter class overlapping. To preserve variations in/around the classes, conventional feature extraction and representation strategies may not work. Therefore, we should investigate unconventional feature representation schemes to develop effective models.
1.5 Objectives

With the above backdrop, in this research work, we propose to design computer vision algorithmic models for the following objectives.

- Classification of tobacco seedling diseases for site specific application of specific agrochemicals.
- Classification of tobacco leaves for harvesting purpose.
- Grading of cured tobacco leaves.
- In addition, we were motivated to build our own datasets of diseased tobacco seedling leaves, tobacco leaves (unripe, ripe and over-ripe) for harvesting purpose and cured tobacco leaves of 12 grades, as there is no publically available standard tobacco datasets.

1.6 Performance Measures

In this section we present different measures that are generally used to evaluate the performance of segmentation and classification models.

Let N be the number of relevant (expected) areas (regions of interest) to be segmented out from an image. Let R be the number of relevant areas segmented and I be the number of irrelevant areas segmented. Let T be the total number of segmented areas and it is given by

\[ T = R + I \]  

(1.1)

Then precision and recall are defined as follows.

- **Precision (P):** Precision is the ratio of the number of relevant areas segmented to the total number of segmented areas.

\[ P = \frac{R}{T} \]  

(1.2)
**Recall (R):** Recall is the ratio of the number of relevant areas segmented to the number of relevant areas expected.

\[
R = \frac{R}{N} \tag{1.3}
\]

Further, to evaluate the accuracy of a segmentation algorithm, one should compare the segmented area with ground truth area using the following region based segmentation measures.

Let \( SG \) be the segmented ground truth area, \( UG \) be the unsegmented ground truth area and \( SNG \) be the segmented nonground truth area. Let \( G \) be the ground truth area and it is given by

\[
G = SG + UG \tag{1.4}
\]

Let \( S \) be the segmented area and it is given by

\[
S = SG + SNG \tag{1.5}
\]

We adopt the following measures in our experimentations.

- **Measure of Overlap (MOL):** This measure is also known as the area overlap measure (AOM) or the Jaccard similarity measure (Elter et al., 2010). It is defined as the ratio of the intersection of segmented area \( S \) and ground truth area \( G \) to the union of segmented area \( S \) and ground truth area \( G \). When the MOL is high, then the probability of segmentation performance is superior.

\[
i.e., \quad \text{MOL} = \frac{S \cap G}{S \cup G} = \frac{SG}{S \cup G} \tag{1.6}
\]

- **Measure of Under Segmentation (MUS):** This measure is defined as the ratio of the unsegmented ground truth area \( UG \) to the ground truth area \( G \) (Elter et al., 2010). Lower the MUS, superior is the segmentation performance.

\[
i.e., \quad \text{MUS} = \frac{UG}{G} \tag{1.7}
\]
• **Measure of Over Segmentation (MOS):** This measure is defined as the ratio of the segmented non-ground truth area SNG to the segmented area S (Elter et al., 2010). Lower the MOS, superior is the segmentation performance.

\[
i.e., \quad \text{MOS} = \frac{\text{SNG}}{\text{S}} \quad (1.8)
\]

• **Dice Similarity Measure (DSM):** Dice similarity measure (DSM) is derived from a reliability measure known as the kappa statistic (Yuan et al., 2009) and computes the ratio of the intersection area divided by the mean sum of each individual area.

\[
i.e., \quad \text{DSM} = \frac{2 \times \text{S} \cap \text{G}}{\text{S} + \text{G}} \quad (1.9)
\]

If the DSM is high, then the segmentation is said to be superior.

• **Error Rate (ER):** The error rate ER is defined as the normalized agreement of segmentation results and the ground truth (Yuan et al., 2009). The ER is given by

\[
\text{ER} = \frac{\text{S} \oplus \text{G}}{\text{S} + \text{G}} \quad (1.10)
\]

In addition, to evaluate the correctness of classification algorithms, one should look into confusion matrix. A confusion matrix is a matrix plot of predicted versus actual classes of the samples.

Let \( k \) be the number of classes. Let \( r_i \) be the total number of samples of \( i^{th} \) class. Let \( c_i \) be the number of samples classified (labeled) as \( i^{th} \) class. Let \( T_i \) be the number of samples correctly labeled as \( i^{th} \) class. Then precision, recall, F-measure and classification accuracy are defined as follows.

• **Precision (P):** Precision of the classifier model with respect to \( i^{th} \) class is the ratio of the number of samples correctly labeled as \( i^{th} \) class to the total number of samples labeled as \( i^{th} \) class. The precision of the classifier model with respect to \( i^{th} \) class is given by
\[ P_i = \frac{T_i}{c_i} \] (1.11)

- **Recall (R):** Recall of the classifier model with respect to \( i^{th} \) class is the ratio of the number of samples correctly labeled as \( i^{th} \) class to the total number of samples of \( i^{th} \) class. The recall of the classifier model with respect to \( i^{th} \) class is given by

\[ R_i = \frac{T_i}{r_i} \] (1.12)

- **F-measure (F):** F-measure is the harmonic mean of precision and recall and it is given by

\[ F = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \] (1.13)

- **Classification Accuracy (CA):** It is the ratio of correctly classified samples to the total number of samples classified.

\[ CA = \frac{\sum_{i=1}^{k} T_i}{\sum_{i=1}^{k} r_i} \] (1.14)

In the thesis, we use all the above mentioned measures to evaluate our proposed segmentation and classification models.

### 1.7 Outline of the Thesis

In chapter 2, details on datasets of tobacco crop on seedling diseases, harvesting and grading are presented. The preprocessing stages that we have followed while creating these datasets during the course of research work is also presented.

In chapter 3, a novel model for classification of tobacco seedling diseases is presented. A novel method of lesion area segmentation is proposed to support the effective classification of tobacco seedling diseases. Evaluation of the proposed segmentation method using region based performance measures is also presented. In addition, classification models based on K-NN classifier and PNN classifier are devised for the
diagnosis of disease type on tobacco seedling leaves. The results of an extensive experimentation on our own tobacco seedling dataset are also presented.

In chapter 4, we propose two different models viz., filter based model and texture based model for classification of tobacco leaves for the purpose of harvesting. The filter based model is designed based on combination of first order edge extractor and second order filter. An algorithm for detection of maturity spots on leaves is also presented. A method of finding the degree of ripeness is proposed for effective classification of tobacco leaves. The texture based model is designed based on texture features such as LBP, LBPV, GLTP, Gabor response and Wavelet decomposition. Fusion of these texture features in different combinations is studied. Feature selection on these fused vectors is envisaged. The corresponding classification model is also designed based on K-NN classifier. Efficacies of the proposed models are demonstrated by conducting series of experiments on a considerably large dataset.

In chapter 5, a novel method of representing cured tobacco leaves by the use of interval valued symbolic feature vector is presented for the purpose of grading of cured tobacco leaves. The Munsell color features of cured tobacco leaves are used for representation. The novel interval valued representation is based on the minimum and maximum of respective individual features. In addition, we also explore a method of approximating the interval valued data by the use of mean and standard deviation of respective individual features (Guru and Prakash, 2009). The corresponding symbolic classifier is also devised. Results of the experiments on our own grading dataset are tabulated to bring out the significance of the proposed model. Qualitative comparison of the proposed model with other well known models for grading of cured tobacco leaves is also presented.

In chapter 6, overall summary, the major contributions of the research work presented in this thesis and avenues for further research work in the proposed directions are presented.