Chapter 1

Introduction

Agriculture is fundamental to food production and supply. Insufficient food supply is one of the most crucial challenges in recent years due to the increase in world population and reductions in agriculture [11, 12]. Precision agriculture has received increased attention in food production and supply, due to its numerous environmental (e.g. reduces herbicide effects) and economical (e.g. enhances breeding process) advantages. It is also improves productivity of agriculture, thus so to meet the food insufficiency challenge. Precision agriculture has been studied in plant properties, types, and conditions. This information was then used for stress detection and monitoring [13], weed mapping [14, 15], disease management [16, 17], and enhancing the breeding process [18, 19, 20]. Several studies have reported that precision agriculture better utilises agriculture resources [11]. However, the traditional techniques in agriculture require substantial time and effort. As an example, human expertise is required to identify disease behaviour and characteristics (visually or analytically) before applying herbicide to infected plants [17, 21]. For the breeding process, visual inspection and analysis are needed to manually select superior seeds or crops. This is time-consuming, seed and crop-destroying, and highly error prone [19, 20]. Traditional stress detection techniques are also slow and labour-intensive [22]. Water stress detection involves drying the plant in an oven to measure the concentration of water. For weed mapping, information (e.g. species, location, and growing stage) is collected manually by weed experts, which is also expensive and labour-intensive [15].

The need for automated, efficient, reliable, and non-destructive precision agriculture techniques has increased with high demands for agriculture products and resources. Recently, remote and proximal sensing, two popular methods, have been used to overcome traditional precision agriculture technique limitations [15]. The use of remote sensing has been discussed in the literature for several applications, such as plant classification, mapping, disease detection, and status identification (e.g. stressed and controlled) [23]. Remote sensing also has the potential to collect plant samples in a large area over a short time period in a non-destructive manner [15]. However, remote sensing is less preferable in detailed plant data analysis due to the limitation in spatial resolution; i.e. the data has been captured from satellites or UAV platforms. Moreover, these platforms are "heavily dependent on the weather conditions" [15]. Proximal sensing is preferable in this kind of precision agriculture, since it solves the spatial resolution issue; i.e. it collects high-resolution images. It is more precise than traditional precision agriculture techniques though it covers a smaller area and it is slower than remote sensing. In the past, broadband sensors (i.e. multispectral sensors), which mainly cover visible bands, have been widely used in both remote and proximal sensing platforms to develop vegetation indices [24, 25]. A normalised difference vegetation index (NDVI) is a typical example of these indices, used to estimate the coverage of green and leaf areas. However, most indices are sensitive to seasonal characteristic changes of the plants and soil, due to the limitation of the spectral bands.

The evolution of sensor technology has brought significant benefits to the field of remote and proximal sensing [26]. The development of hyperspectral sensors, for example, triggered a considerable amount of interest in exploring innovative scientific quests. It senses different regions of the electromagnetic spectrum (e.g. ultraviolet, visible, infrared, etc.) in a large number of detailed narrow band spectra [1, 27, 28]. In other words, the main difference between hyperspectral imaging (HSI) and other conventional imaging is the spectral resolution, i.e. the number of bands and how narrow those bands are [28, 29]. Since HSI captures a vast amount of data, an effective approach for the analysis, e.g. using machine learning techniques, is needed to extract the relevant information, such as stress and disease properties, from images [30]. HSI involves the convergence of spectroscopy and remote imaging technologies. It captures the optical properties of a target with multiple spectral representations [31]. It also has been utilised in several applications, especially in precision agriculture, due to the numerous environmental and financial merits [1]. These merits include controlling the herbicide process, reducing the resistance of weed species to herbicide, reducing the pollution effects of the herbicide to the environment, avoiding plant stress to maintain a normal growth cycle, and preventing disease separation of healthy species [13, 16, 32]. Several approaches have used hyperspectral images in the last few years to study plant properties, types, and conditions. For example, several hyperspectral-based vegetation indices (a list was given in [17]), have been developed to classify plant type, identify stress levels, and detect plant or crop diseases [13, 14, 15, 16, 33]. The spectral pattern, or spectral signature, which it is a function of wavelength, has also been used to characterise plant properties, or types, or conditions [34]. Unique and detailed spectral signatures can be extracted from hyperspectral images, compared to the multispectral and used in the analysis. Both examples show potential for analysing hyperspectral images of a plant; however, discriminating weeds species, identifying different stress sources, and detecting plant diseases are still challenging. Limited wavelengths, or bands, or channels are used in vegetation indices (i.e. the wavelengths may not be distinctive enough to address the problem) and the entire spectrum is used for the spectral signature (i.e. high dimensional data is provided but not all bands may be relevant to the problem). Machine learning has a great ability to ease precision agriculture challenges and much work has been conducted in the literature to present machine learning techniques that improve the analysis, i.e. better usage of the available information [30].

Recently, the need for robust and effective hyperspectral analysis approaches has increased, because a significant amount of data is being generated, and not all data necessarily contains useful information relating to the problem being examined. It is difficult to analyse the information directly from pixels values [1, 27, 28]. Machine learning is a useful tool for the analysis since it reduces the generated data to the most discriminative information. Note that machine learning techniques are applied based on the scale and complexity of the problem. There is an increase in using advanced machine learning techniques, such as feature extraction, feature selection, deep learning, anomaly detection, feature level fusion, and ensemble learning to improve and develop new hyperspectral-based analysis approaches. These approaches involve spectral or spatial information to analyse data collected from HSI systems. The approaches are referred to as spectral, spatial, and spectral-spatial analyses. For the spectral analysis approach, multivariate analysis methods (e.g. feature extraction, feature selection, deep learning, etc.) are used to reduce or eliminate the dimensionality and collinearity problems of hyperspectral images [31]. Such methods are crucial, since not all spectral bands contain useful information and this must be addressed. Moreover, a systematic method for retaining distinctive spectral features that considers feature relevance and relationships is preferable. A systematic extraction or selection of the distinctive features solves the limitation issue in spectral vegetation indices as well as the irrelevance problem in the use of the entire spectral pattern. In addition, it reduces the dimensionality of the collected data and improves its interpretation, thus enhancing the performance of classification [31]. It is worth noting that spectral data has been utilised extensively to analyse hyperspectral datasets, because it has enough information for discrimination [35, 36].

Alternatively, useful information can also be extracted from image textures and used as either standalone or complementary features for the analysis [37]. Texture contains valuable information about the pixels' structural arrangement and relationships. For the independent case (standalone), the arrangement and adjacent pixels' intensities are used for the analysis, thus providing an important base for description and recognition, giving insightful information about the surface properties of the images.The techniques for analysing textures can be broadly categorised into statistical, structural, transform-based, and model-based [38]. All techniques have similar aims, but each has a unique form to explore image textures. The first uses the distribution of grey levels, and the second employs existing texture properties. The third transforms textures into another domain and uses the transformed characteristics to describe textures, and the fourth uses empirical models to define image textural properties. In contrast, the advantages of combined properties (spectral and texture) have been considered to investigate a problem from different points of view. Previously, texture properties have not been included in the analysis because of the mixing issue, especially in moderate spatial resolution images [35, 36]. Currently, the ability to acquire high spatial resolution images has improved the mixing issue. This improvement resulted in increased spectral variability within a class but decreased variability between classes [36, 39]. Several studies have highlighted the importance of incorporating spectral and texture features and the effect of the combined features on classification accuracy [35, 36]. In addition, various attempts have been made to combine different image features using simple concatenation and/or confidence scores (feature level fusion), or decisions using hard and/or soft merging techniques (decision level fusion), or the features and rules in a single framework to improve local and overall classification accuracy [40]. Although the importance of various fusion levels for classification accuracy has been highlighted, selecting a robust and effective level remains challenging.

One-class classification, typically used for novelty detection, is a special case of the classification problem. Samples are only available for one class (called normal), while samples of other classes (termed abnormal) are sparsely distributed, if not absent [2].

One-class classification can be defined as the process of classifying unseen testing samples via modelling samples from a well-distributed class. Hence, the constructed model reflects the coverage of the normal class and the classification performance is measured based on the ability of that model to recognise unseen samples with similar characteristics to those used for model construction [6, 9, 41, 42, 43, 10]. One-class classification techniques can be categorised as density-based, distance-based, reconstruction-based, domain-based, and information-based [9]. These techniques have been utilised in remote sensing, industrial applications, and medical monitoring, within which obtaining abnormal samples are impractical and can take a long time or lead to losses [2]. The role of one-class classification was investigated in this thesis for precision agriculture, since the datasets do not cover all plant properties and conditions (e.g. diseases and stress levels). It is also the first use of one-class classification for precision agriculture.

1.1 Research Scope

The thesis aims to develop advanced machine learning-based analysis approaches for classifying plant types and conditions for precision agriculture utilising spectral and spatial features (individually and collectively) from hyperspectral images. Recent advancements in HSI systems have heightened the need for machine learning techniques as an efficient analysis tool, since a large amount of data is being generated and it is difficult, if not impossible, to analyse the information directly from the pixel values. Advanced machine learning techniques have been employed to extract the most significant image features and combine them or their decisions to further enhance classification performance. It also has been used to extend the analysis to unbalanced data cases (uncertainties) to overcome the limitation, e.g. missing samples, limited conditions, etc., in the collected data, i.e. more realistic. Note that the methodology has been tested with data captured in a controlled environment (laboratory) and reported significant improvement. Several factors need to be considered when applying the resulting methods in field environments such as registration problem, blurring issue, illumination non-uniformity, and atmospheric effect. Using image registration algorithms, deblurring techniques, suitable enclosures on the cameras, and atmospheric correction techniques prior to analysis may mitigate the effects of these factors, thus a possibility of applying the methodology in the field environment.

The research considers feature selection only for dimensionality reduction and extracting distinctive features from both spectral and texture information. Proposing a new feature selection algorithm was also outside the scope of this research. Rather, it was intended of developing a framework exploring useful spectral and texture features for discriminating plant conditions. For classification, the thesis focused on support vector machine (SVM) classifiers (conventional and one-class).

1.2 Aims and Objectives

The research described in this thesis aims to develop advanced machine learning-based analysis approaches (robust and effective) for precision agriculture classification using the spectral and spatial image features. Advanced machine learning techniques are used to develop approaches that extract distinctive image features (to reduce data dimensionality and improve its interpretation) and combine the extracted features or their decisions to improve the overall classification performance. In addition, the analysis approaches are developed in controlled environments and tested using data captured from different hyperspectral systems (hand-held and laboratory-based). The objectives of the research in this thesis are:

- To identify the capabilities of feature selection algorithms to improve the classification performance of plants under different conditions and to address the limitation of empirical spectral indices. The effect of an optimal subset of features, selected by feature selection algorithms, on classification accuracy will be demonstrated and compared to empirical spectral indices. The systematic selection may shed light on attributes that differentiate crops and conditions.

- To validate the use of the most distinctive spectral and spatial features for the context classification of hyperspectral datasets captured by several sensors. Classification performance of systematically selected elements will be compared to the existing empirical indices.

- To assess the use of combined rules as compared to the use of a single rule and to evaluate classification accuracy of plant or crop types and conditions. It will also investigate the use of merged decisions in several feature selection algorithms and appraise classification accuracy as compared to the application of a single feature selection rule.

- To appraise the usefulness of existing novelty detection techniques for unbalanced data cases, i.e. other than the cases considered in this thesis. Classification performance of unbalanced data cases will be compared to conventional cases using both imaging and non-imaging (i.e. captured by spectrometer) datasets.

- To verify the importance of different image features for classification, e.g. spectral and spatial information combined using feature level, or decision level, or feature-decision level fusions. The performance of combined features will also be compared to the use of individual features.
- To develop a unified hyperspectral-based analysis framework using both spectral and spatial properties, wherein adaptive feature selection, novelty detection, ensemble learning, feature fusion, and decision combination are incorporated. Performance of the developed framework will be evaluated for precision agriculture using imaging datasets.

1.3 Research Methodology

The purpose of this research is to develop a robust and effective analysis approaches based on several advanced machine learning techniques and to verify the advantages of the incorporated techniques in classifying hyperspectral images for plants under different conditions.

The research starts with exploring existing procedures in the literature for studying plant types and conditions. Advanced machine learning techniques are then studied and their advantages on classification performance are tested using benchmark machine learning datasets from the University of California, Irvine (UCI) machine learning repository [44]. To address precision agriculture challenges advanced machine learning techniques are adopted, due to their usefulness. These challenges necessitated proposing novel approaches incorporating dimensionality reduction techniques, distinctive feature extraction algorithms, and local, or global, or local-and-global fusion schemes. By assembling advanced machine learning techniques, carefully, it is possible to improve the analysis, thus enhancing classification performance. Several hyperspectral datasets of various plants or crops under different conditions are obtained from collaborators (e.g. the University of Bonn [45] and the University of Sheffield[1]) and collected locally using HSI systems that operate in controlled environments following the required data acquisition procedures. Testing on the collected datasets is performed to evaluate the effectiveness and robustness of the proposed approaches for

[1]This dataset is unpublished yet - Veys *et al.* in the list of publications.

classification. Comparisons against the existed methods in the literature using a quantitative criterion, classification accuracy, are carried out to justify the performance of the proposed approaches. The results of the proposed approaches are also verified and validated against some benchmark datasets (e.g. Indian Pines and FR spectrometer - described in Chapter 5, Subsection 5.3.1). Upon successful verification and validation of the experimental results, seven research papers have been written to validate the proposed approaches externally. Three research papers were submitted to peer-reviewed international journals (two published and one under revision) and four research papers were disseminated and presented at international conferences.

1.4 Main Contributions

The key contributions of this thesis are summarised in Figure 1.1, which depicts the procedures followed to enhance classification accuracy and to develop a unified framework for spectral-texture classification of hyperspectral datasets. In seeking to achieve the objectives of this thesis, three general approaches for hyperspectral image based plant classification have been developed:

1. Approach-I: Combining decisions of several feature selection algorithms: This framework merges various feature selection decisions (described in Chapter 4 and detailed in [27]). The novelty consists of incorporating decisions from different algorithms under a centralised rule to enhance the overall classification accuracy. This approach has been proposed, because the criteria for selecting relevant features among the algorithms vary, resulting in generating different optimal subsets of features with inconsistent classification accuracies [27]. Experimental results of this approach show marked improvements in classification accuracy compared to the individual feature selection algorithms.

2. Approach-II (described in Chapter 5 and [2]): Approach-I has been extended to cope with uncertainties (i.e. unbalanced) in the data (e.g. missing samples or labels). The reason behind this extension is that not all cases, crop types, and conditions, are covered in the datasets. A domain-based novelty detection has been used to extend the conventional SVM classifier, and the classifier output is further calibrated into class probability [2]. The findings show the advantages of the extension for condition monitoring and abnormality detection when mostly samples of one class are available, i.e. highly unbalanced data situations. The

applicability and validity of this extension to a wider range of condition monitoring applications have been proved using several HSI datasets collected from different devices.

3. Approach-III: We have developed a unified framework that integrates different image features, e.g. spectral and spatial, and decisions. A model-based texture analysis technique, Markov random field, has been used to extract textural properties, while feature selection has been used to select the most distinctive spectral and textural parameters. Different fusion levels have been investigated and tested with the goal of developing a robust and effective analysis framework. Experimental results indicate that it is more beneficial to combine different image elements for precision agriculture than to use individual elements. Employing decision level fusion helps selecting one of the best performing rules. In addition, using feature and decision fusion techniques tends to be more powerful and robust than individual features or classifiers. Detailed information about this framework is presented in Chapter 7 and in [28, 46, 47].

Finally, approaches I - III were examined using imaging and non-imaging hyperspectral datasets for plant types and conditions classification [1, 27, 28, 46, 47]. The analysis suggested that the approaches I - III shed light on the attributes that better differentiated plants, properties, and conditions. All approaches were tested in laboratory conditions, i.e. controlled environment. However, the developed approaches can be applied to field environments if a suitable enclosure is applied to the hyperspectral cameras to reduce noise and other limitations (e.g. registration, atmospheric, and blurring) are carefully addressed. Initial trials with a portable in-house built HSI device were conducted, and results were promising.

1.5 Thesis Outline

The thesis chapters are organised as follows:

- Chapter 2 reviews literature on HIS, including common terminologies, advantages, limitations, calibrations, pre-processing, and analysis techniques as well as applications. It also highlights how HSI was used in precision agriculture.

- Chapter 3 provides background on feature selection models and algorithms. It introduces feature-level fusion and its approachess. In addition, a comparison

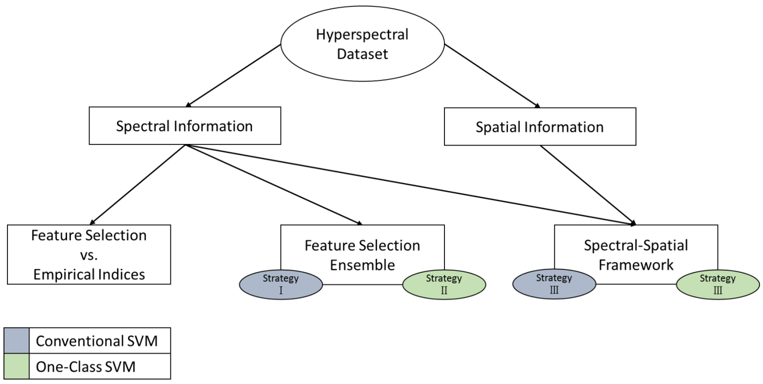

Figure 1.1: Summarised schematic diagram of the developed approaches.

in classification performance between several feature selection algorithms and empirical indices is presented.

- Chapter 4 explains the concept of ensemble learning and decision-level fusion in detail. A framework is proposed for combining decisions of several feature selection algorithms and classification performance is compared to the individual feature selection algorithms.
- Chapter 5 surveys novelty detection techniques. It highlights the approach followed to extend feature-ensemble framework to unbalanced data situations. A comparison in classification performance between conventional and one-class classifiers of the framework is also given at the end of this chapter.
- Chapter 6 presents the analysis from a texture point of view. It begins with reviewing different texture analysis techniques followed by detailed information on the Markov random field (MRF). Classification performance of such techniques is evaluated on datasets similar to the ones used for spectral analysis approaches.
- Chapter 7 describes integration efforts, i.e. the proposed unified framework. It addresses merging approaches of features, and decisions levels by highlighting the benefits of each. Different image features and decisions are combined for more efficient and robust classification performance.
- Chapter 8 concludes the thesis with suggested directions for further implementation and development of universal spectral-texture analysis techniques within precision agriculture.