UNIT 5: Leaf Disease Recognition and Yield Prediction

5.1.Introduction:

Crop infection detection is critical for crop growth monitoring and safeguarding the quality of production. For this purpose, optical recognition can be affectivity utilized by specialists for monitoring possible changes in crop leaves, therefore a highly experienced and specialized background. New techniques handling data mining by AI is able to enhance trustworthy the credibility of a possible infection recognition and thus can be featured into actionable insights to enable interventions.

Methods using AI combined with image feature analysis are capable of providing a more precise and effective tool for crop disease detection. Crop infection recognition using visual information is regarded challenging, more specifically, on its automated form. This task is often hard to be tackled, because of the special characteristics in terms of morphology and but also because of lighting conditions. Crop infection evaluation is a critical step for adopting accurate and efficient crop management practices encompassing predictive algorithms and various means of treatment.

Fungal diseases are regarded responsible for severe yield degradation, yield low productivity and financial losses, ranging between 5 and 80% depending on the severity of infection, ambient factors related to climate and terrain, and lack of resistance due to susceptible genotype. It is crucial to focus on the relation that exists between various unexpected deviations in the characteristics of plant leaf morphology and the variety of the environmental factors that would act as are possible stress factors to a specific crop that demonstrates stress symptoms .

7.2 State of the art:

Various techniques are used in the present targeting on identifying plant infections by applying digital image processing. Crop disease identification was achieved in sugarcane leaves by threshold segmentation to isolate the infected leaf location and triangle thresholding to obtain the lesioning area, reaching an average accuracy of 98.60% (Patil & Bodhe, 2011).

Texture feature extraction has also been used for plant disease detection. Patil and Kumar (2017) introduced plant disease detection approach base on texture feature extraction including morphological features, uniformity, and relative associations derived by estimating the co-occurrence matrix of the gray image of corn leaves combined with color extraction, giving a trustworthytrainingfeature based setfor image enhancement and improved detection.

Rothe and Kshirsagar (2015) employed a Back propagation approach for classifying diseased leaf images of cotton. During the training procedure, seven invariant moments were extracted from three leaves images depicting infections from three different diseases respectively. The utilized snake segmentation algorithm achieved a classification of 85.52%, providing an efficient solution for set apart the area of interest (the infected one). However, the proposed method is characterized as time consuming. Zhang, Wu, You, and Zhang (2017) proposed a leaf disease detection procedure in cucumber, by setting apart the infected leaf area through an efficient combination of k-means clustering and color and shape feature extraction, obtaining a score of 85.7% correct recognition. A similar approach has been presented by Guo, Liu, and Li (2014). In this approach texture and color features were combined by a Bayesian approach. The investigated diseases where downy mildew, anthracnose, powdery mildew, and gray mold. The utilized model achieved accuracy rates of 94.0%, 86.7%, 88.8%, and 84.4% respectively. Vianna, Oliveira, and Cunha (2017) proposed a pattern simulation approach for recognizing the globally threatening of late blight in tomato leaves. In this paper, 20 networks were tested, from which the best network produced a prediction of 97.99%. Fiel and Sablatnig (2013) have diversified leaf infection detection by applying Bag of Words with SIFT descriptors in 5 different tree species, attaining an accuracy of 93.6%.

Meunkaewjinda, Kumsawat, Attakitmongcol, and Srikaew (2008) presented an automated crop infection diagnosis detection system which utilized various artificial intelligent algorithms in infected vine leaves. Selforganizing feature map and back propagation neural network has been applied in order to detect the colors of vine leaves. Additionally, an altered modified SOM has been applied for segmenting the image and support vector machine is used as a classifier, demonstrating a performance of 86.03%. Self-organizing feature map is also used to detect disease of cotton leaves.

Kebapci, Yanikoglu, and Unal (2011) developed a plant retrieval system taking into consideration the color, shape and texture characteristics by employing the color histogram, the color co-occurrence matrix and a modified Gabor method approach. The experiment has been performed for crop type recognition in domestic plants reaching 73% for successful recognition.

Pethybridge and Nelson (2015) have presented an IOS application called ‘Leaf Doctor”, capable of discriminating the possibly infected from the healthy plant tissue areas. In this approach, eight colors denoting the healthy tissue areas form the threshold assisting the recognition of the healthy ones. With respect to the six corresponding infections, the algorithm’s sensitivity was accessed according to targeted range of 10 color corrected images attaining a R2 >0.79.

Nevertheless, some of the main drawbacks of this approach is that for the image processing, a black background is required. The black background has proven to be most of the times responsible for the majority of misclassifications since it can be falsely mixed up with alike colored pixels linked to infection symptoms. Moreover, considering the fact that the samples were destructively taken, makes the method less credible. The employed algorithm was difficult to come to a trustworthy conclusion in variable ambient field conditions and alterations, as a result more stable and trustworthy algorithms are required.

The current case study demonstrates a novel application of recognizing four different health status including healthy, downy mildew, powdery mildew and black rot in different tissue samples through One Class Classification. The presented application is able to assess images obtained in real conditions without additional processing and can decide with certainty on the occurrence of infection even at its early stage appearance. The current approach is comprised of a learning procedure with training data relate to each one of the four different crop status. A previously unseen and unlabeled feature vector is used as input to a one-class classifiers committee, triggering activations. In the occasion that multiple activations take place, then a conflict occurs since more than one classifiers are regarded as contenders of the new feature vector ownership. The current case study demonstrates high generalization potential regarding the leaf plant disease identification in several crops, where the training set was comprised solely of vine leaf samples.

5.3 Materials and methods:

The Local Binary Pattern (LBP) is atexture analysis approach,that ableto label pixels by defining their proximity limits, forming a binary outcome. The LBP approach takes advantage of its capability of maintaining a stable behavior to the upcoming gray scale level deviations that occur, such as illumination and image processing under complex real-time conditions, proving its computational potential to be implemented in several commercial applications.

The LBP operator has been introduced by Li, Wu, Wang, and Zhang (2008) and Llado, Oliver, Freixenet, Marti, and Marti (2009) considering texture features including pattern including the relative pattern’s strength applied with a 33 grid, where the center value denotes a threshold.

The LBP code is formulated as presented: the thresholded values are scaled by the corresponding weights of the pixels. Since the neighborhood is defined by eight pixels, a set of 28 ¼256 discrete labels are produced, corresponding to the relative threshold’s gray levels and remaining pixels of the grid. The contrast indicator (C) is defined as the subtraction of the mean of the pixel levels that lie below the threshold defined from the mean of pixel levels larger or equal to the threshold. In the case that the thresholded pixel levels are equal to zero or one, the contrast value is equal to zero. Fig. 7.1 depicts an illustration of LBP operator function.

6	5	2
7	6	1
9	8	7

example

1	0	0
1		0
1	1	1

thresholded

1	2	4
128		8
64	32	16

weights

Pattern = 11110001 **LBP =** 1 + 16 + 32 + 64 + 128 = 241

C = (6+7+9+8+7)/5 – (5+2+1)/3 = 4.7

Fig. 7.1 Illustration of LBP operator function

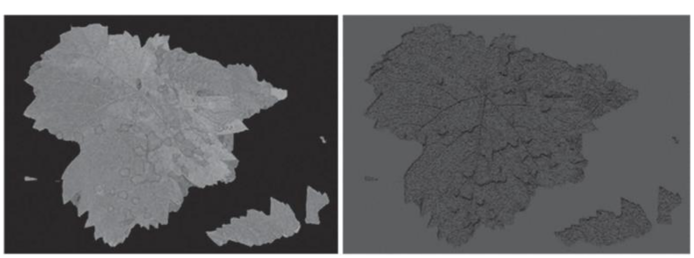

Fig. 7.2 (A) Hue channel illustration of a vine leaf (Pantazi, Moshou, & Tamouridou, 2019). (B) LBP leaf image of vine crop

The LBP operator is able to transform an image into a matrix of integer levels that definethe detailed local structure ofthe image (Fig. 7.1). These levels or their derived statistical operators like histogram, are the parameters used for producing image analytics. The LBP operator is mainly applicable to binary images as well as multi-channel images, video streams and multi-dimensional data. The hue channel is derived from image of the leaf as depicted in Fig. 7.2A. The LBP transform application on the Hue channel derived of the segmented image produces an LBP leaf image, as illustrated in Fig. 7.2B.

5.4 Application of LBP in disease recognition of infected plants:

5.4.1 Image segmentation:

As a first step, an image of the diseased leaf that manifests visual symptoms is obtained by a smartphone or tablet (Fig. 7.3A). Afterwards, image segmentation takes places aiming to obtain the leaf area and exclude the image background. Then, a Hue Saturation Value (HSV) transform is imposed to the segmented area (Fig. 7.3B). The GrabCut algorithm operation is summarized in the following steps: 1. The central image points correspond to foreground while the surrounding regions correspond to background. Then, a rectangle is formed including the target region while the internal pixels are recognized as not known and the external ones are denoted as known.

2. An image segmentation is performed by applying Gaussian Mixture Models (GMMs) to the foreground and background utilizing the Orchard-Bouman algorithm to create the clusters.

3. All pixels are classified as foreground or background through the allocation of Gaussian component corresponding to the foreground or the background GMMs. 4. The arising pixel sets yield the learning adaptation, targeting on the creation of new GMMs. 5. A graph is constructed, activating the GrabCut algorithm for assigning a new foreground class. 6. The former steps (4–6) are iterated until all the pixel sets are classified. The GrabCut algorithm creates K components of multivariate GMM corresponding to the background. A similar procedure is followed for K components corresponding to the foreground. The GMM components are labeled according to the color statistics corresponding to each cluster.

5.4.2 Creation of LBP histogram:

The GrabCut algorithm is applied individually on various single channels of the initial image because of the LBP operator is applied in a single channel. On the initial RGB image two separate transforms options were tested: the first transform obtained in HSV format while the second transform obtained gray scale image. From the HSV transform it has become apparent that the LBP histogram applied on the Hue channel, yielded the highest performance in comparison to the gray scale transform in relation to the detection of disease crop symptoms. The LBP operator manages the labelling of the pixels corresponding to the obtained images based on their mutual distance in the Hue channel, and consequently takes in to account the textural characteristics concerning contrast and Hue variation as illustrated in Fig. 7.3B. The LBP histogram depicts the appearance rate of Hue levels from 0 to 255. For avoiding noisy values in the histogram, the 256 bins has been reduced to 32. An illustration of the reduced histogram is given in Fig. 7.4, where the x and y axes, denote the amount of bins and the allocation of pixels per bin (%) respectively. The inhomogeneity of symptoms in symptomatic leaves induces deviations in texture of a local nature which are evident which appears in the LBP histogram as higher pixel counts in specific bins (Fig. 7.4). As it is shown in Fig. 7.4, the healthy leaf status is associated with subtle alterations in the local texture structure. The pixel count in certain bins in the LBP histograms corresponds to other local deviations that are associated to the collapse of leaf structure produced by the pathogen invasion. Equally, the black rot occurrence provokes high pixel count in the first bin and an additional peak in the sixth bin. In the case of powdery mildew occurrence, lower pixel count is demonstrated in the first and a peak in the ninth bin. This is explained by the contribution of the pixel count to the leaf structure collapse that finally lead to the discrimination of black rot from powdery mildew symptoms.

5.5 Segmentation technique:

The current method is able to achieving successfully generalize disease ditection by using for the training of OC-SVMs a small amount of vine leaves samples, (8) arbitrarily chosen, with respect to the four different health conditions. The originality of the of the presented study lays on the GrabCut's algorithm ability to isolate the leaf area from that belonging to the foreground. In the occasion of multiple leaves present to the image even from other crop species, the GrabCut has proven capable of isolating efficiently the individual sample that is validated. In the current case study, no special conditions were necessary for the image acquisition, because the algorithm can isolate the region of the leaf from any natural background, in field conditions. A significant advantage of the current method is that it is nondestructive, which works efficiently without the need of detaching the leaf from the crop. These characteristics constitue to proof that the presented method is robust and operational, because the functionality of the method is not affected by variations in shading, leaf orientation and ambient lighting. Regarding calibration, no camera settings were needed like focus and shutter settings. The afore mentioned features prove that the methodology is user friendly, highly functional and adjustable to a variety of alternative scenarios in different case studies. The operation of the GrabCut algorithmis robust against variable RBG values due to the use of Gaussian Mixtures.

5.6 Classification process and the features extraction process:

The current case study achieves an accurate recognition of specific leaf diseases by means of novelty detection. In some cases, the phenology of some diseases appears to be similar in terms of occurrence, meaning that for the same crop there are also detected as outliers. The close distance between the feature vector and the one class classifier spheres explains the operation of the algorithm. The characterization of both infected and healthy crops expressed in HSV features and more specifically the Hue channel of healthy crop images is the cornerstone is that defines the structure the OC-SVM for vine leaves. This behavior is closely related to the feature that has been utilized in the LBP histogram. The LBP is responsible for the robustness against variations to ambient factors including scaling, translation and rotations or illumination fluctuations. The crucial information that is associated to the crop health status is exploited by the LBP histogram as variations in textural characteristics that emanate from the symptom and the visual distribution of the symptoms. The variation of the background is overcome due to ability of the GrabCut to remain unaffected by the possible intrinsic factors that could possibly affect the segmentation process arising from the image background and acquisition factors. The acquisition factors related to orientation and lighting are confronted by the LBP histograms thanks to their variability to these factors. However, various diseases or nutrient stresses can cause similar symptoms that cannot be easily identified by the validated OC-SVMs. Even in this case the presented conflict resolution can act in an independent manner, by exploiting the distance of the feature vector to the support distance so as to determine the class. The proposed technique unites the AI's assets with progressive image analysis aiming to extract image characteristics that identify the textural alterations correlated to crop health status. The proposed approach exploits the synergistic effect between OC-SVMs reaching high precision in assessing crop health status through conflict resolution arising from the between opposing classifiers. The proposed technique can be exploited towards the determination of crop health status in order to decide the best management option in the framework of precision crop protection.

Yield prediction:

6.1 Introduction: Artificial neural networks (ANNs) have gained popularity an effective tool for offering solutions to a wide variety of different case studies of biological and agricultural background. Their effectiveness emanates from their ability to model complex relationships between observation data from sensors and predicted variables without relying on assumptions about the model structure hence they can predict the real nature of the nonlinear relation between input and output data. This allows the definition of arbitrary nonlinear relations that arise in real world problems like PA and are associated with crop status and other environmental factors (Uno et al., 2005).

Yield prediction is a major challenge in precision agriculture, closely associated to the adoption of best management practices, crop pricing and security. The yield prediction allows assessing the variability and the reasons that evoked this variability so that the parameters affecting yield including proper irrigation, fertilization, crop protection and field interventions to be applied site-specifically customized to the crops requirements. Various techniques and methodologies have been developed to predict crop yield in agriculture.

Drummond, Sudduth, Joshi, Birrell, and Kitchen (2003) employed more diverse methodology for calibrating ANNs with the same training set for predicting the yield. They concentrate on training performance, generalizing on new data, and exclusion on outlier data in order to decide which is the best methodology. The authors experimented with different variants of backpropagation for the training procedure, proving that all the forms of trainable neural networks performed significantly better than the linear ones, and that rprop was more effective than simple backpropagation.

Yu et al. (2010) proposed an group of feedforward ANNs to perform fertilization predictions. They indicate that two problems arise when a feedforward network is utilized in this way. Initially, they discovered that associating a maximal output yield before processing results in substantial regarding the rates of the fertilizer application. It has been also concluded that the utilization of a single ANN, results in low forecast performance and generalization potential.

The authors suggested an ANN where the input are the nutrient concentration and rate of fertilization while the prediction target is the yield. They calibrated various neural networks by using backpropagation through a bagging process and clustered the networks by using the k means algorithm. Following that, they picked up an ANN, representing each cluster to construct a group of ANNs. The combining weights were determined by using Lagrange multipliers with a set of constraints that force the sum of the weights to become equal to unity. Following that, a nonlinear objective function was constructed from the group output and applied nonlinear programming to find the optimal rate.

Kuwata and Shibasaki (2015) demonstrated a deep neural network (DNN) approach by using as input several parameters including, the canopy surface temperature, Absorbed Photosynthetically Active Radiation, water stress index and NDVI, to be fed to a DNN and a Support Vector Machine Regression. By employing the DNN, the RSME is equal to eight for predicting the yield in corn.

You, Li, Low, Lobell, and Ermon (2017) applied a CNN combined with a Long-Short Term Memory (LSTM) network aiming to classify histograms emanating from multispectral remote sensing images. This CNN has attained the best RMSE values, equal to seven.

While considering different ANNs architectures that are found in literature, SOMs are the most applicable and effective machine learning tools, capable of offering solutions to arising nonlinear data analytics case studies (Marini, 2009). Furthermore, they are able to provide insight by functioning in a unsupervised way, similar to data clustering.

Data mining is an independent field of study that usually applies machine learning techniques. Pantazi et al. (2016) developed Supervised Self Organizing Maps methodology, seeking to perform an analysis on sensor data and construct an updated knowledge content. The presented approach assigned input nodes that were associated to the main parameters of wheat crop production cultivation.

The SOM used that data to predict the wheat yield and productivity. Some of the non-linear prediction models utilize traditional soil sampling (e.g. 1 sample per ha) and destructive laboratory methods which are laborious, time demanding and of high cost. An alternative approach proposed by Mouazen (2006) relies on high sampling resolution with a nondestructive, spectral soil sensor.

This sensor has proven to estimate key soil parameters relevant to crop yield with variable accuracy, including soil organic matter content (SOMC), cation exchange capacity (CEC), moisture content (MC), total nitrogen (TN), pH, calcium (Ca), clay (CC), magnesium (Mg), organic carbon (OC), phosphorous (P), and plasticity index (PI) There have been several approaches, focusing on data fusion of characteristic soil properties highly associated to crop growth indicators like NDVI to forecast yield in arable crops.

An approach that would be interesting to follow concerns the visualization of the yield affecting parameters in order to discover correlations between them and the yield trend. The current case study focuses on crop yield prediction by adopting a novel approach, relying on a hierarchical SOMs with enhanced supervised capability.

The presented machine learning algorithms enable the fusion of high resolution multi-layer data on soil and on crop, by constructing a sensor fusion neural network model which learns to estimate the geo-spatial arrangement of wheat yield, with high performance in comparison with current techniques. These algorithms facilitate an enhanced visualization potential of soil, crop properties and yield productivity

8.2 Materials and methods:

In the current case study, three Self Organizing Map architectures including CPANN, SKN and XYF by employing Supervised Learning to find possible relations between precision farming observations and yield productivity levels. For the application of this methodology, physicochemical soil properties were acquired with the use of an on-line vis-NIR sensor which was assimilated with crop growth parameters by implementing a sensor fusion algorithm.

8.3.2 Soil parameters affecting yield:

By considering the launch of visible and near infrared (vis-NIR) spectrophotometers entering the market together with chemometrics software, the employment of vis–NIR spectroscopy has been widely adopted for assisting soil analysis. Further developments enabled the relative to vis-NIR spectroscopy applications to measure more accurately and effectively several soil parameters like the Moisture Content (MC) pH, Soil Organic Matter (SOMC), Total Nitrogen (TN) and Organic Carbon (OC).

A variety of calibration procedures have made possible the parallel acquisition of soil parameters estimations. Shibusawa, Made Anom, Sato, & Sasao, 2001 has presented an on-line vis-NIR (400–1700 nm) sensor for the estimation of pH, MC, NO3-N, SOMC.

Mouazen (2006) has proposed a simpler design compared to the one presented by Shibusawa et al. (2001) which was characterized by the lack of sapphire window optical configuration. The sensor system was capable of providing accurate estimations regarding the MC, TC, pH, TN, Ca, Mg, available P and cation exchange capacity (CEC) for several soil types across the European area .

On-line soil estimations took place in the Horn's End field during crop harvesting period of summer 2013. Data acquisition was performed in parallel transects with mean velocity circa 1.5–2 km/h. A mobile AgroSpec fiber type, mobile, vis–NIR spectrophotometer with a spectral range between 305 and 2200 nm was used for soil diffuse spectra acquisition.

The source soil spectra data has been registered and retained for temporal analysis. While performing the online data acquisition, soil samples were gathered for the assessment of sampling correctness of the relevant soil parameters. A collection of 60 soil samples were acquired and subjected to laboratory testing following standard protocols.

Partial Least Squares Regression (PLSR) has been employed for the estimation of soil properties, specifically Ca, Mg, total N, CEC, OC, MC and pH. Further details are provided by Kuang and Mouazen (2013). The predicted values were obtained after interpolation on 5m5m grid, matching the sampling locations of 8798 points that correspond to the NDVI and crop yield

8.3.3 Prediction of crop yield:

For the prediction of crop yield three hierarchical SOM models including SKN, XYF and CPANN were employed by utilizing Matlab.

The dataset corresponding to the investigated soil parameters were acquired with the help of an online soil sensor. Then, they were combined in the same vector with the NDVI values obtained by the satellite imagery and historic yield data, resulting to 8798 feature vectors. The feature vectors were formed through the fusion of both soil and crop properties.

To prevent bias occurring during the training procedure, the data vectors that were attained from fusion, were transformed in a way that their mean variant was removed and the standard deviation was equal to one.

The steps followed included the subtraction of the mean vector and the division with the help of the standard deviation operating on each one of the training dataset samples. To perform the yield prediction, the fusion vectors were supplied to the three models. The values of the yield were grouped in three classes each one containing 2933 samples in ascending mode, belonging to low, medium and high yield class.