The Technology Uses in the Determination of Sugar Beet Diseases

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Abstract

Early detection of plant disease and pest attack that cause substantial yield and economic losses in agricultural production and taking the necessary precautions on time make a great contribution to the reduction of product loss. Therefore, it is necessary to determine the outbreak, severity, and progress of the disease and pest in a timely and accurate manner. There is a need for faster and practical innovative methods that reduce human errors in the identification of plant diseases, disease severity, and progress of the disease, especially in wide production areas. Agricultural applications of drones have increased significantly in recent years because of their greater availability and the miniaturization of hardware such as GPS, sensors, cameras, inertial measurement units, etc. Drones mounted with camera are a cost-effective option for capturing images covering areas with disease and pest. However, visual inspection of such images can be a challenging and biased task, specifically for diseases and pests detecting. Image processing and deep learning methods have been used extensively for automatic determination and recognition of plant leaf diseases. In the present study, drones, equipments, and multispectral, hyperspectral, thermal, and RGB cameras used for the diagnosis of sugar beet diseases and image processing and deep learning techniques, and possible future of technological developments are discussed. The

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technological, economic, and vital effects of using these methods on human life and the environment are discussed.

Keywords

Sugar beet · Disease detection · Leaf spot disease · Powdery mildew · Beet Necrotic Yellow Vein Virus · Drones · Image processing · Deep learning

30.1 Introduction

Sugar beet (*Beta vulgaris*, L) is a biennial plant which produces an enlarged root and hypocotyl in the first year. In the enlarged root, it stores sucrose that provides energy for flower and seed production in the next season. Sugar beet typically is cultivated in the temperate zones. Mainly, it is cultivated as a spring crop. The main producing regions are the European Union, the United States, the Russian Federation, Turkey, Ukraine, Iran, Japan, and China (Bradshaw et al. 2010). World annual sugar beet production area is 4.609.434,00 ha and average yield is 60.419 ton/ha (FAO 2019). Sugar beet plant is produced for the sugar contents of its roots. Primarily, the sugar manufacturing industry uses sugar beet as a raw material. The molasses produced as a by-product of the sugar beet processing are used in the food and alcohol industry. Sugar beet production is very valuable for the farmers and industry (Bradshaw et al. 2010).

The rapid developments in information technology resulted in progress of mechanization, automation, and control technologies in agriculture. So that, intelligent machines and production systems take over the traditional production methods (Ozguven 2018). In recent years, with the increase in technological equipment such as sensors, actuators, signal conditioners, processors, and the decrease in costs, the widespread use of advanced design methods such as deep learning, machine learning, artificial intelligence, modeling, simulation, agricultural robots, and smart agricultural machinery has been improved and they have been used instead of traditional production methods in agriculture (Özgüven and Közkurt 2021).

30.2 Sugar Beet Diseases

Sugar beet is a herbaceous dicotyledonous plant which is grown for sugar production (Bradshaw et al. 2010). The average yield is 60 tons/ha and yielded 8 tons of white sugar per hectare depend on climatic factors and crop rotation strategy (Bradshaw et al. 2010; Pervin and Islam 2015). As it is seen in other cultivated plants, various viral, bacterial, and fungal pathogens attack and reduce the sugar beet yields and cause economic losses at different plant stages. While *Rhizoctonia solani, Phoma betae, Pythium ultimum, and Aphanomyces cochlioides* cause damping off, *Cercospora beticola* (Cercospora leaf spot), *Erysiphe betae* (powdery mildew), and *Peronospora farinosa* (Downy mildew) cause leaf diseases. Beside that, *Fusarium oxysporum f. sp. spinaciae* and *Fusarium oxysporum f. sp. betae* cause Fusarium yellow and root rot diseases (Duffus and Ruppel 1993; Walker 2002; Skaracis et al. 2010). Due to the diseases and pests, sugar beet yield losses amounted to 37.1%. Economically important and common diseases of sugar beet are Cercospora leaf spot and Rhizomania diseases caused by Cercospora beticola and Beet Necrotic Yellow Vein Virus (Benyvirus BNYVV), respectively (Rush et al. 2006; Ward et al. 2007; Skaracis et al. 2010).

Cercospora leaf spot disease of sugar beet (*Beta vulgaris* L.), caused by the fungus *C. beticola* Sacc., is the most damaging and widespread disease of sugar beet leaves. Under favorable environmental conditions, it leads up to 50% yield reduction (Shane and Teng 1983; Wolf et al. 1998; Rossi et al. 2000). The symptoms of the disease are individual circular leaf spots (3–5 mm). The spots are darker brown to reddish-purple borders with light brown centers. In conditions of high humidity, black sporulating can be observed on spots. With disease progression, spots will coalesce, with leaves turning yellow and then brown while remaining attached to the plant. *Cercospora beticola* survives on plant debris, volunteer plants, and in seed. Wind and rain splash distributed the pathogen spores during growth. The disease control measures include use of resistant beet cultivars and fungicide application (Agrios 2005).

Rhizomania is another serious disease of sugar beet that is seen worldwide. In susceptible sugar beet cultivars, root yields and sugar contents can be reduced up to 90% (Johansson 1985; Rush et al. 2006; Ward et al. 2007). *Polymyxa betae*, the soil protozoan (family Plasmodiophoraceae), transmits the pathogen virus (Tamada and Asher 2016). The virus might survive in P. betae cystosori for more than 15 years (Johansson 1985). The symptoms of rhizomania are root bearding, stunting, chlorosis of leaves, vein yellowing followed by upright foliage with elongated petioles. Later on, dark brown bearded roots can be observed. The BNYVV is spread by movement of soil, primarily on machinery and the plant roots. Irrigation water may spread the vector fungus and also the virus. Mainly, the disease management relies on host plant resistance (Agrios 2005; Tamada and Asher 2016).

To reduce the yield loss, rapid and accurate detection, determination, and identification of the plant disease severity are required. Recently, several researchers have explored the benefits of image processing and machine learning techniques for disease identification in whole plants and leaves (Ozguven and Adem 2019). The new techniques such as image processing and deep learning might be used in assessment of the sugar beet cercospora leaf spot and rhizomania diseases.

30.3 Drone and Equipments

A drone is an Unmanned Aerial Vehicle (UAV) with the four or more propellers, which can stay stable in air and perform vertical takeoff and landing. Depending on the technical features needed, drones can be designed variously (Tan et al. 2015). Being more complex and having more parts than drone increase the expense of

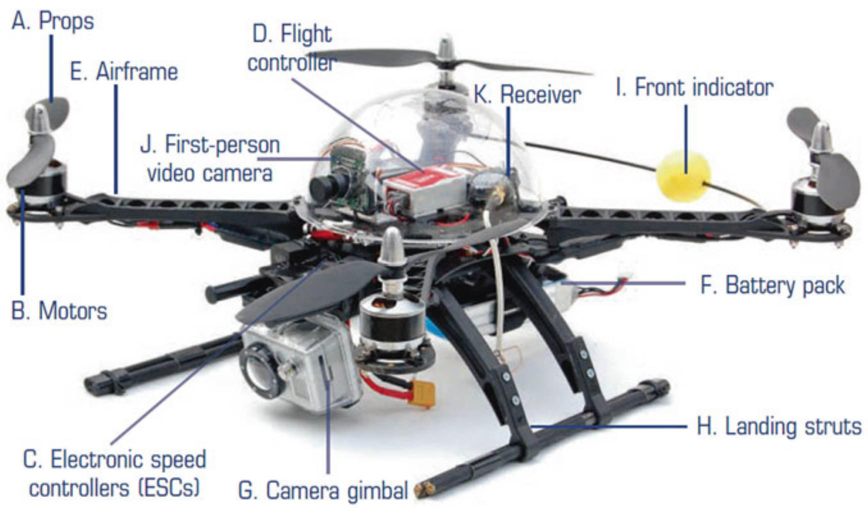

Fig. 30.1 Components of drone (Baichtal 2016)

system installation of UAVs. In drones, however, drone might be used immediately after purchasing drone together with the apparatus without the need for any other costs. The drones are preferred in agricultural applications because of their ease of use and lower cost (Özgüven 2018). The most preferred drones are quadrotor drones shown in Fig. 30.1 (Ozguven 2018). The examples of different forms of rotors are tricopters, hexacopters, and octocopters. The number of optional rotors might be increased, thereby increasing the capacity of the drone.

The quadrotor has an advantage over other rotors because of its highest maneuverability, such as vertical takeoff and landing capability in hazardous areas. However, a quadrotor cannot fly for long periods because of high power consumption (Merç and Bayılmış 2011).

Key attributes that enable UAV operation are as follows (Clarke 2014):

1. Ability to go and return to the target position within the operation area,
2. A set of controls and maneuverability over the UAV attitude, direction, and speed of movement,
3. Remote data streams to maintain timely awareness of movement, attitude, and location, and,
4. Sufficient power to sustain movement, to perform the controls, and to run sensors and data streams, for the period of the flight,
5. Situational awareness through tracking operational space,
6. Ability to avoid collisions and navigate through obstacles,
7. Robustness to withstand various dangerous situations, such as bird strike, stroke of lightning, turbulence, and wind-shear,
8. Ability to fly in all atmospheric conditions.

30.3.1 Components of Drone

Although drones are designed with different technical features in accordance with their usage areas, their basic components are given below (Fig. 30.1) (Akyüz 2013; Johnson 2015; Baichtal 2016; Szabó et al. 2018):

(a) Propellers: Propellers used by mechanically connecting to motors for spatial movements of drones are generally made of carbon-fiber material. For example, the propellers of a quadcopter typically consist of two standard and two pusher propellers rotating in opposite directions.

(b) Motors: Although DC or AC motors might be used, electric motors are used most commonly, brushed or brushless direct current motors. So as to do the same amount of work on all rotors, the same kind of motor is used. Compared to brushed motors, brushless motors are more widely used owing to their advantages such as quiet operation, long life, much more efficiency and less wearing parts, no electrical noise, no regular maintenance, and ability to run at higher speed and high torque in a lower voltage range.

(c) Electronic speed controllers (ESCs): ESCs convert DC to AC for brushless motors and also trigger the motors' power supply. One is used for each engine. ESCs' firmware might be changed to create different motor behaviors. For instance, ESCs are often configured to slow down the motor rather than stopping abruptly.

(d) Flight controller: The flight controller controls the entire electromechanical system of the drone. It assists manual flight with certain autonomous functions. For instance, many flight controllers have an accelerometer sensor that keeps the drone level. The flight controller provides movement and stabilization in the desirable direction by changing speed of the motors according to the data from the sensors. Thus, the drone can stabilize itself even if the engines are given different pusher.

(e) Airframe: The airframe consists of components, such as including motor booms alongside an enclosure or platform for housing the electronics. The drone ought be light and thin enough to lift off and tough enough not to break in a minor accident. Carbon-fiber, plastic, wood, and aluminum alloy materials are generally preferred in the construction of the main body.

(f) Battery pack: Usually a LiPoly battery, the drone's battery pack keeps the propellers turning while also powering whatever electronics are onboard.

(g) Gimbal: Gimbal is a rotating platform on which a camera is placed. Servomotors allow the operator to turn and angle the camera during flight.

(h) Landing struts: Landing struts are used to prevent damage to the camera or other protuberance under the drone. Drones without cameras, on the other hand, do not have landing struts and the drone lands with its entire airframe.

(i) Front indicator: Especially the front side of the drone must be known by the operator. For this, different colored lights, LEDs, reflective materials, or colored balls are used.

(j) Video camera: Cameras with different resolutions are used that send images to a tablet with radio waves. HD cameras are often used for mapping, surveying, and image captured such as multispectral cameras, hyperspectral cameras, thermal cameras, laser scanners, synthetic aperture radars.
(k) Receiver: Commands given by the pilot to move the drone are converted by the receiver into the flight controller instructions. A five-channel communication module is sufficient for propeller acceleration control and control mode (Tx/Rx) for yaw, roll, and pitch angles.

30.3.2 Cameras and Sensors Used with Drone

Due to the easy use of drones and the competences of the cameras and sensors mounted on them, they are often used in agriculture for detection, monitoring, inspection, control, evaluation, decision making, classification, mapping, sensing, forecasting, research, management, etc. and have been widely used in missions. For this reason, different drone designs are made in terms of the need and suitable sensors and cameras are mounted to it according to the way of working. In addition, newly improved software and hardware such as cameras and sensors provide smart behavior development and autonomous operation to drones. Thus, drones are aware of itself and its surroundings during the flight and can decide on its own to perform the desired movements in predetermined situations and apply the decision itself. While there is a wide range of cameras and sensors produced that could be used with drones, there are also a wide variety of cameras and sensors of different brands and models from the same type of cameras and sensors.

30.3.2.1 Optical Cameras

Aerial images captured by human crewed aircrafts have higher quality than satellite images, but this method is quite expensive. However, similar high quality images can be captured with drones which are more economical solution (Radoglou-Grammatikis et al. 2020). Visible band sensors like optical cameras are extensively used for photogrammetric applications using UAV, mainly aiming for orthophotos, orthomosaics, 3D models, and surface and elevation models generation (Georgopoulos et al. 2016). In addition, data obtained using drone images or sensors in drones can be effectively superimposed with maps prepared with satellite images, terrestrial observations, or terrestrial sensors (Franzen and Kitchen 2011). Technical specifications of optical cameras are the sensor type and resolution, the pixel size, the frame rate, the focal length to be used, and the shutter speed in addition to the weight of the camera/lens system. The most commonly used types of optical cameras are CCD and CMOS DSLR cameras, while mirrorless cameras are becoming increasingly popular, mainly because of their small weight (Georgopoulos et al. 2016).

Numerous images can be captured during a drone flight. These images can be evaluated with the eyes of experts, as well as with the developed image processing software, comments and evaluations could be performed about the images. In addition, artificial intelligence-based software that can perform real-time and automatic evaluation has been improved recently, and new methods and models have been improved to obtain better results, and development studies are continuing rapidly to apply these software in new areas. There are plenty successful studies on this subject, especially with the deep learning method.

30.3.2.2 Multispectral Cameras

Multispectral cameras are used widely in agriculture to obtain information about plant growth, soil, and water properties. Plants reflect especially in the near infrared (NIR) region. The NDVI (NDVI = (NIR − R)/(NIR + R)) values obtained by proportioning the NIR band with the red band give information about green vegetation. Thus, when the NDVI value approaches 1, the plant is healthy, while the NDVI value approaches 0 the plant is weak or stressed. The band values vary as to the characteristics of the developed sensor. For instance, the multispectral bands of the Landstat satellite are as stated below: 0.45–0.52 μm (blue), 0.52–0.60 μm (green), 0.63–0.69 μm (red), and 0.76–0.90 μm (NIR).

The spectral range and precision required to profile materials and organisms that only hyperspectral sensors can provide and these features are not available on RGB and/or NIR sensors. For such high-resolution spectroscopy, first satellites and then manned aircraft were used. But these techniques are very expensive and have availability limitations. More recently, the remote sensing technology, which is popular and cost-effective, has been developed using small-sized and lightweight sensors integrated into drones. The ability of hyperspectral sensors to measure hundreds of bands adds to complexity given the huge amount of data obtained. To reach the right multispectral data, both calibration and corrective tasks should be performed in the preflight and postflight phases (Adão et al. 2017). Some commercially available multispectral sensors combine high-resolution RGB cameras with 4, 5 or 6 spectral bands, providing high spatial resolution suitable for bundle adjustment and extraction of geometric parameters. These cameras offer individual multispectral sensors equipped with high-class interference filters and provide high-precision spectral measurements that could replace ground-based spectral reference measurements in the forthcoming (Szabó et al. 2018).

30.3.2.3 Hyperspectral Cameras

Hyperspectral image sensing has the ability to resolve several hundred spectral bands in the region from visible light to short-wave infrared and may make it possible to ensure more phytobiological information by analysis of continuous spectral properties, compared with multispectral analysis. Hyperspectral analysis may provide information on productivity and stresses of plants, biochemical and mineral components in living plants, and soils, classification of species, soil types, and parts of plants (Omasa et al. 2006). Because of this, for each the recorded pixels cover the entire spectrum. However, while there are special multispectral sensors designed for utilization in UAVs, it is not simple to obtain a hyperspectral sensor that might be used directly in UAVs. Also, the integration into UAVs with these cameras is complicated for the captured frames that do not overlap. Therefore, much more attention and care must be given to the acquisition of images and its post-processing (Horstrand et al. 2019).

30.3.2.4 Thermal Cameras

Thermal infrared imaging (a passive spectral imaging method) is effective for early diagnosis of plant stresses along with measurement of surface temperatures of soils and plants (Hashimoto et al. 1984; Omasa and Aiga 1987; Omasa 1990). Image analysis of the energy balance on canopy and the leaf provides phytobiological information on stomatal response and evapotranspiration (Omasa and Croxdale 1992; Jones 1999; Omasa 2002). Although low-cost thermal cameras are widely available today for UAVs, spatial resolution is quite limited. Also, thermal camera lenses have a significant radial distortion (Boesch 2017). Unlike optical image solutions, thermal imaging requires special georeference procedures. Basically, it is difficult to find natural ground control points (GCP) in lower-resolution thermal images. Therefore, artificial control points are required, using mainly aluminum as the material. Aluminum GCP show a sharp boundary in the thermal image, and automatized identification algorithms already exist for them (Szabó et al. 2018). With these algorithms, orthophotos are created by processing thermal data with Structure from Motion (SfM) photogrammetry (Maes et al. 2017). A general three-step framework for processing thermal images with UAV data is presented below (Turner et al. 2014):

1. Image preprocessing, which is the removal of blurry imagery and transformation of all images to 16-bit TIFF files where all images have the same dynamic scale range to ensure that a temperature value corresponds to the in-rem digital number value in all images.
2. Image alignment, where the initial estimations of the image position are obtained from the onboard GPS log file and the time stamp of each image.
3. Spatial image coregistration to orthophotos such as RGB is made by manually adding GCP with known location, from processed RGB images or RTK GPS.

30.3.2.5 Light Detection and Ranging (LiDAR)

Lidar sensors determine the distance of a surface or an object using laser beams. It works similarly to how radar technology works. The difference is that inside of radio waves, laser pulses hit the surrounding objects and the distance value is calculated by the reflection time. 3D point information of the area measured with lidar can be acquired in a very short time, at the desired frequency and with high accuracy (Özgüven 2018). Therefore, the range is determined by the delay in the travel and return of the light waves to the target. The nanosecond pulses used in this pulsed lidar generally have high instantaneous peak power. Therefore, centimeter resolution can be achieved in single pulses over a wide aperture window (Royo and Ballesta-Garcia 2019). Lidar sensors might be grouped into two groups based upon the platforms they are installed on: Airborne Lidar Sensors (ALS) and Terrestrial Lidar Sensors (TLS). Still, their utilization for UAV systems is still challenging in the way of size and weight (Colomina and Molina 2014).

30.3.2.6 Synthetic Aperture Radar (SAR)

SAR technology is a method used to obtain higher resolution images in direction of the flight with a smaller antenna length. By acting the radar antenna throughout the desired aperture, it takes measurements at certain time intervals and collects these data simultaneously to form a synthetic aperture. Thus, a large synthetic aperture equal to the actual physical aperture is created (Irak 2009). SAR technology is a traditional method implemented by satellite systems. Although it has not been fully implemented in UAVs, work is in progress toward this result. The main problem with the concept is that this type of survey is mainly affected by the diverse weather conditions (Szabó et al. 2018).

30.4 Disease Detection with Technological Methods

Plant diseases cause economically important income losses in agricultural production all over the world (Savary and Willocquet 2014; Avelino et al. 2015). To reduce crop loss, plant disease severity must be determined accurately and rapidly. Therefore, determining the outbreak, severity, and progression of diseases in a timely and accurate manner is of great importance for an effective integrated disease management (Bock et al. 2010). The naked eye assessment of diseases is a subjective task, which is prone to psychological and cognitive phenomena, can lead to bias, optical illusions, and ultimately to error (Barbedo 2016). There is an immediate need to develop faster and practical methods, which could reduce human errors in the identification of plant diseases, their severity and progress, especially in large production areas (Altas et al. 2018).

In the event of a disease, plants exhibit visual signs in the shape of colorful spots with different shape and sizes according to the type of disease and in the shape of lines seen on stems and different sections or organs of the plants. These symptoms alter color, shape, and size while the disease progresses. With image processing methods, colored objects might be distinguished, and the severity of plant diseases might be determined. Besides image processing methods, expert systems might be improved to allow instant disease diagnosis with machine learning methods (Ozguven 2020). Recently, potential use of image processing and machine learning methods for disease detection in whole plant and/or different plant parts (leaves, stem, fruit, and such) has been comprehensively studied by many researchers (Ozguven and Adem 2019). Plant diagnosis with image processing methods and computer vision is still new and many alternatives are required to be discovered to minimize several associated problems. The images are trustworthy representation of the scene, and thus, could allow the advancement of accurate and powerful analysis tools (Barbedo 2016). However, visual monitoring is labor-intensive and time-consuming. Existing field investigations with spectral sensors mounted on UAVs are rendered possible to monitor wide areas in a little while. On the contrary, traditional remote sensing platforms with manned aircraft and satellites, UAVs, perform greater flexibility and an immensely high level of detail (Schoofs et al. 2020). In addition, drones provide effective disease management during the whole season in agricultural areas without disturbing the plants by supplying high-quality images for disease identification (Altas et al. 2018).

30.4.1 Image Processing Technique

Image processing technique is a method used to turn into the image in the photo or video frame obtained with a camera, scanner, or sensors to digital format after recording and to extract some useful information from these digital data with the aid of a set of algorithms. In this technique, images are rearranged with various processes and meaningful results are obtained finally with these processes. During these processes, it is tried to obtain the descriptive parameters that represent the important data in the image. By this way, defining and separating the features to be measured, correcting image defects, enhancing the visibility of certain features, and thresholding them in the background are performed.

During the obtaining of images from plants under real growing conditions, problems might occur because of sunlight and shadows. Therefore, these issues should be taken into account. In addition, methods that increase the visibility of related parts or features might be used to extract the necessary information from the image with respect to the aim of the image processing. Therefore, the choosing of relevant features within the image is the first stage of image processing. With this selection, several brightness values in the original image can be defined. Thus, pixels in the chosen range are brought to the foreground and all other pixels are taken to the background. Also, the image can be displayed by distinguishing it as a two-level image using black and white.

Generally, plant disease severity is evaluated by the specialists using different types of disease severity scales. For example, to determine sugar beet leaf spot disease severity (*Cercospora beticola* Sacc.), three different scales (0–9, 1–5 and pictural scales) are performed (Table 30.1, Fig. 30.2) (Vereijssen et al. 2003; Schmittgen 2014; Anonymous 2017). Then, the percent disease severity is computed with the Townsend and Heuberger (1943) formula. Disease severity (%) = $\Sigma(n \times V/$

Table 30.1 The 0–9 disease severity scale for sugar beet leaf spot disease (Anonymous 2017)

Scale No.	Description
0	Whole plant is healthy
1	Onset of disease: Appearance of first stains on outer leaves
2	Increase in number of stains on outer leaves
3	The stains appeared also on the intermediate leaves outside the central leaves
4	Spots coming together apparently
5	Large dead zones on the leaves
6	Large dead zones on the leaves
7	Dead parts in minimum half or more of the palms of the outer leaves
8	Dead leaves in nearly all of the outer leaves and large dead areas in middle leaves
9	Forming new leaves in plants

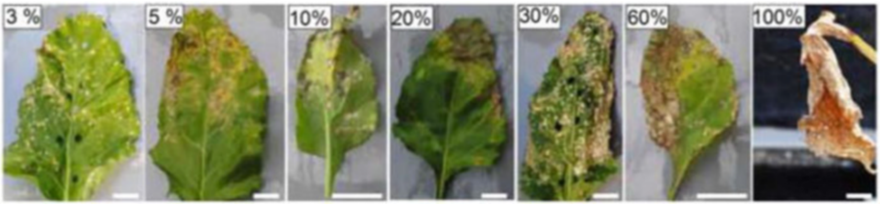

Fig. 30.2 Pictural scale for sugar beet leaf spot disease (Schmittgen 2014)

Fig. 30.3 An example of original sugar beet leaves images

$Z \times N) \times 100$. Where, n: represent number of plants with different disease severity scale, V: scale value, Z: the maximum scale value, N: evaluated total number of plants.

To explain image processing methods, the study performed by Altas et al. (2018) is summarized below. In this research, images were captured under natural light using drone. The symptom image segmentation on the leave is the most crucial process for the disease identifying using image processing techniques. At this stage, pixels were classified into K classes in accordance with a set of features by K-means clustering algorithms. First, data entry was made by entering the sugar beet leaves images to the program. Leaf image was RGB image (Fig. 30.3).

Color space in RGB images limits image distortions stemming from brightness. Therefore, each image was converted from RGB into L*a*b* color space. Information about the disease in L*a*b* color space is used only in two channels (a* and b* channels). Indicative information about the disease is used in solely two channels (a* and b* channels) in the L*a*b* color space. K-means clustering was used to cluster colors in a* and b* space using Euclidean distances between two colors. K-means clustering allows each point to belong to only one cluster. Thus, each pixel in the image is labeled according to the emerges from K-means clustering. Pixel tag and segmentation outputs are given in Fig. 30.4.

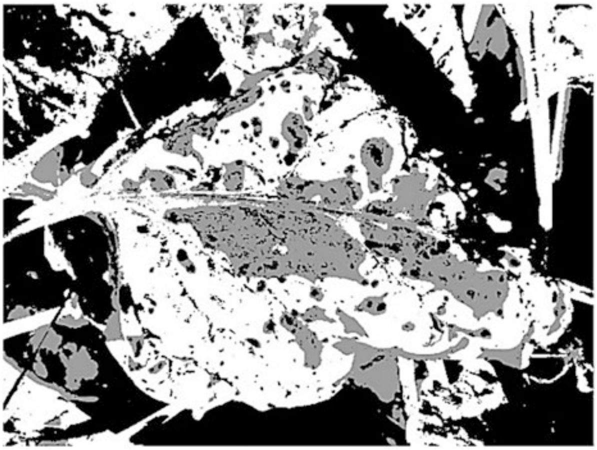

Fig. 30.4 Pixel tagging outputs

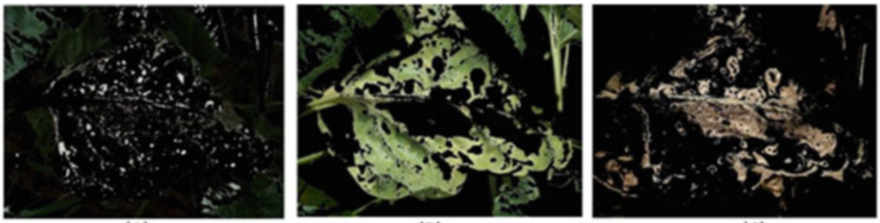

Fig. 30.5 Segmentation outputs: segments of (**a**) black, (**b**) green and (**c**) brown

Using the pixel labels, the pixels in the image were colored as seen in Fig. 30.5 and three images (i.e., $K = 3$) were obtained. The disease image was selected from among three clusters.

Contrast enhancement of color images is done by converting one of the components of the image to a color space with image brightness, for example L*a*b* color space. Therefore, each image was converted from RGB into L*a*b* color space and then, the brightness L layer of the image was worked. The brightness layer was changed with the processed data and the image was reverted to RGB (Fig. 30.6).

The severity of the disease was calculated as the ratio of diseased area to total area.

$$Ak = \sum_{x=1}^{m} \sum_{y=1}^{n} B(x, y) \tag{30.1}$$

$$B(x, y) = \left\{ \begin{array}{ll} 1 & \text{if} \quad B(x, y) \in k \\ 0 & \text{if} \quad B(x, y) \notin k \end{array} \right\} \tag{30.2}$$

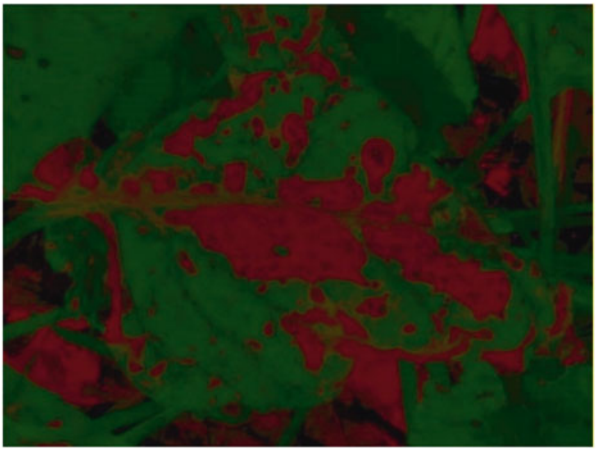

Fig. 30.6 Contrast enhancement

Table 30.2 Comparison of image processing methods and visual evaluation results

Image	Image processing (%)	Visual evaluation (%)	Difference (%)
a	100	100	0
b	48	50	−2
c	42	45	−3
d	21	20	+1
e	80	80	0
f	28	30	−2
g	74	75	−1
h	47	50	−3
i	29	30	−1
j	46	50	−4
k	20	20	0
m	51	50	−1

$$\text{Disease severity }(\%) = \frac{\text{Ak}}{\text{Total Area}} \tag{30.3}$$

where Ak = diseased area, $B(x,y)$ = value at given xth row, yth column of the image identified.

In their study, Altas et al. (2018) used the image processing toolbox module of MATLAB program to examine the presence of leaf spot disease on sugar beet leaves and to assess disease severity in 12 images, indicating the different developmental levels of the disease. The results achieved were given in Table 30.2.

When Table 30.2 is analyzed, it is seen that the results were very close to each other. It was reported that the assessment results acquired by visual evaluation were approximate integer values, the image processing methods results, given the exact value of the diseased area with a sensitivity that cannot be acquired by observation and the research was achieved successfully.

30.4.2 Deep Learning Technique

Deep learning technique is a subcategory of machine learning. Machine Learning is a subcategory of artificial intelligence. In machine learning, various algorithms and methods are utilized to look at historical data, a mathematical model that will determine the complex pattern between the data is determined, and then predictions are made about what is desired to be estimated from the data. In machine learning, processing is done in an only layer, while deep learning processes in many layers at once. The difference of deep learning algorithms from machine learning algorithms is that there is a very great amount of labeled data, and owing to the complicated structure of the data, they need GPU-based computers and hardware with very high computational power to process these data. In machine learning, the relevant features are manually extracted from the images and these features are utilized to create a model that categorizes the objects in images. In deep learning, the related features are automatically ejected from the images and it is learned how to perform a task like classification automatically (Özgüven 2019). Furthermore, using many nonlinear processing layers for feature eject and conversion from a great amount of labeled training data, each successive layer uses the output of the previous layer as an input (Deng and Yu 2014). Deep learning is based upon learning from the representation of the data. In the representation of an image, some features better represent the data such as a vector of per-pixel intensity values or edge clusters and certain shapes (Song and Lee 2013). Commonly used deep learning models, which consist of a set of algorithms and models running on neural networks with multiple layers, are listed below (Özgüven 2019):

- Convolutional Neural Networks (CNN),
- Auto-encoders,
- Recurrent Neural Networks (SRN),
- Deep Belief Network (DBN).

Plant disease observations of experts may sometimes be misleading due to exhaustion of decrement of concentration experienced by the experts. Therefore, visual ratings of the samples gathered from the field should be reassessed later. In addition, there is a requirement for standard field schemes for expert assessments (Bock et al. 2010). Deep learning method offers conveniences for more effective plant protection through diagnosis of plant diseases and owing to monitoring the plant development (Ozguven 2020). The study of the automatic classification and diagnosis of leaf spot disease on sugar beet by the deep learning technique by Ozguven and Adem (2019) is summarized and the deep learning method is explained in practice.

A new 1–3 scale was developed by researchers to determine sugar beet leaf spot disease with the help of expert systems. In the new scale, 0 the whole plant is healthy, 1 low severity of disease, 2 a severe disease, and 3 a low and severe of disease. The 24-bit 1024 $\times$ 576 resolution images received from sugar beet leaves images dataset in the research were performed to determine and classify the disease

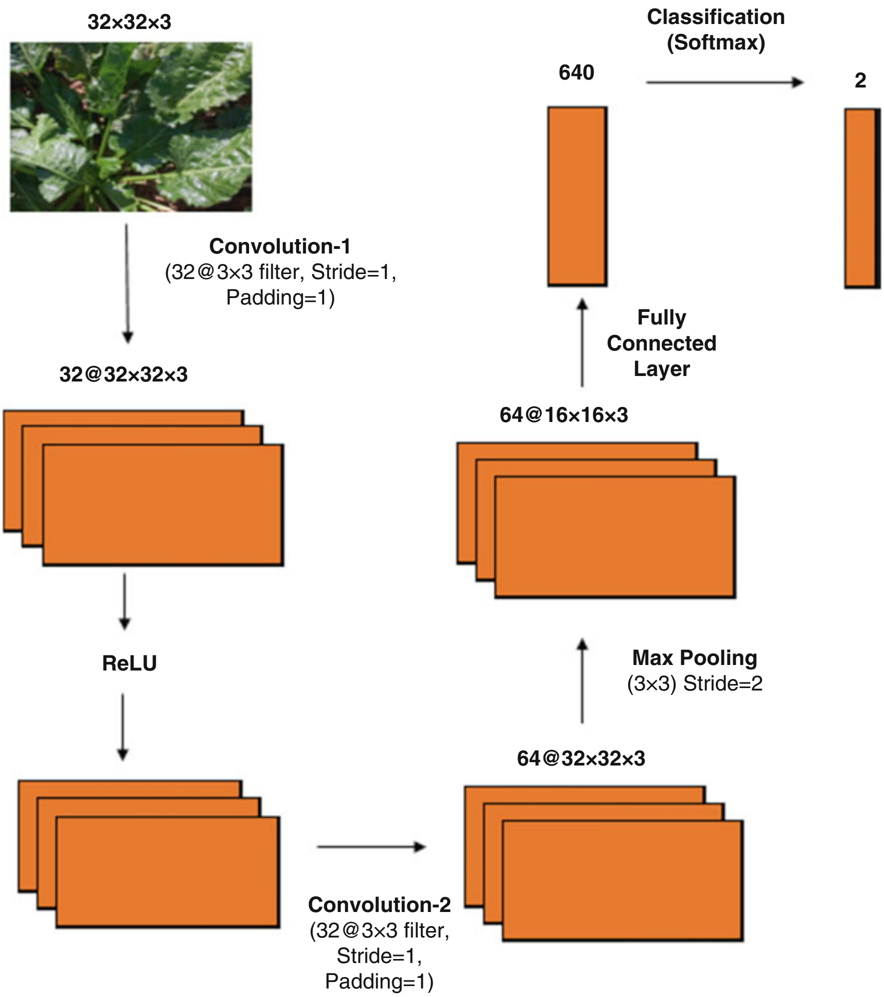

Fig. 30.7 Faster R-CNN architectures

severity as healthy, mild disease, severe disease, or mild and severe mixed disease. The dataset consists of 155 sugar beet leaves images, including 38 healthy, 20 mild diseased, 35 severe diseased, and 62 mild and severe diseased. The Faster R-CNN model was preferred in the study to better determine and classify highly complicated objects. The Faster R-CNN and Updated Faster R-CNN architectures in the research are seen in Figs. 30.7 and 30.8.

The input layer takes the raw data from the network (Figs. 30.7 and 30.8). The raw image was taken as 32 × 32 × 3. The convolution layer is used for feature extraction of the leaf images. The first convolution layer uses 32 different 3 × 3 filters with 1 stride and 1 padding. The rectified linear unit layer (ReLU) is the

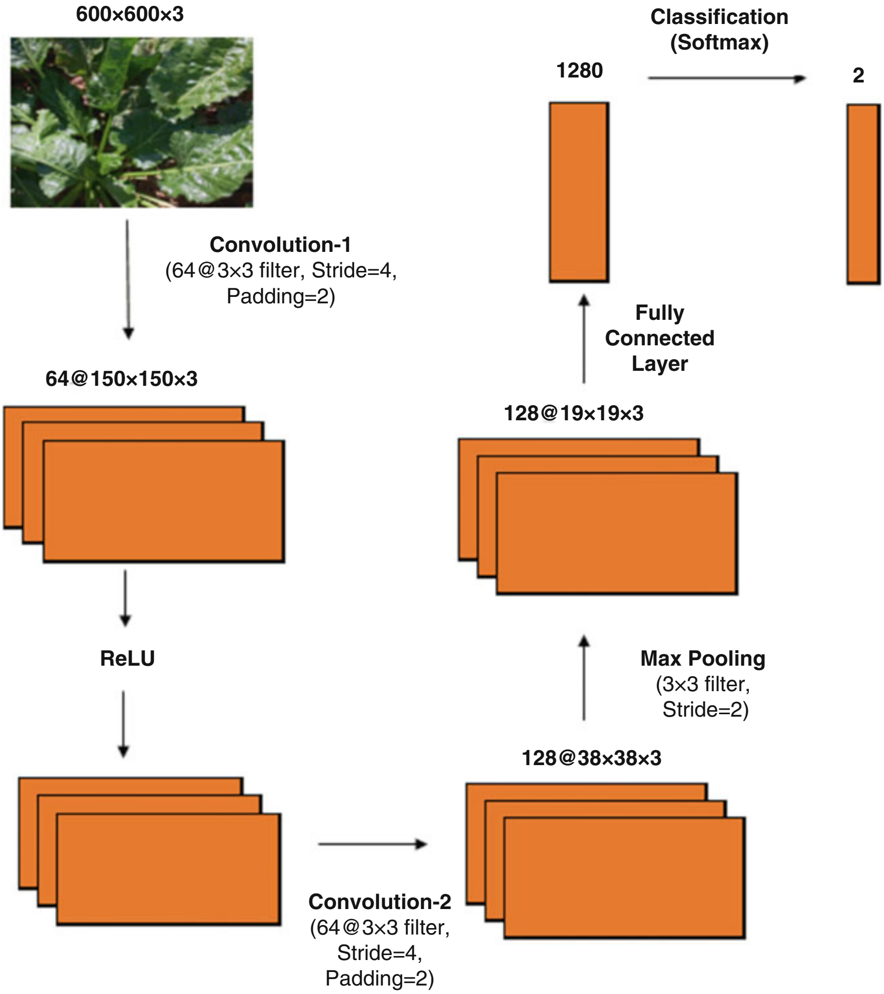

Fig. 30.8 Updated Faster R-CNN architectures

usually used rectifier unit for neuron outputs. There is max pooling to decrease the input size (width × height) for the next convolution layer after the ReLu layer. After the max pooling layer comes a 64-node fully connected layer. This layer connects to all parts of the previous layers. Then there is the classification layer where the classification is done. The last layer is the softmax classifier. This layer is a generalization of the logistic function that could be used for multiclass classification. It gives estimated probability of each class.

In the updated Faster R-CNN model, the input image size is 600 × 600 × 3. In this model, by setting the input image size higher than in the Faster R-CNN model, it was possible to determine insensible diseased areas. Updated Faster R-CNN convolution layer uses 64 different 3 × 3 filters with 4 stride and 2 padding. In addition, the number of filters has been increased to 64 to get comprehensive information about the image. Thus, the number of stride has been increased to 4. For better diagnosis of the diseased areas in the corners of leaves, the padding size was also increased to 2. Accuracy of the classification process was developed by aid of 16-node fully connected layer. Weights were optimized through trainings performed by aid of a heap size of 64, a momentum of 0.85, and a weight reduction of 0.001.

Ozguven and Adem (2019) in their research provided the results of applying deep learning methods to sugar beet leaf images which are given in Fig. 30.9. It was seen that healthy areas were misclassified due to shadows in some images, and diseased areas could not be detected in some images due to reflections. However, disease detection was better with Updated Faster R-CNN architecture. This shows that it was crucial to adjust the parameters in the CNN architecture according to images to which the Faster R-CNN model has been applied. Table 30.3 shows the confusion matrix and Table 30.4 shows the sensitivity, specificity, and accuracy values.

As can be seen in Table 30.3, 111 out of the 117 sugar beet leaves images containing the disease were correctly classified by the proposed model. There was only 1 incorrect classification in 38 images without disease. This demonstrates that the specificity values of Updated Faster R-CNN approach were higher than the sensitivity values as seen in Table 30.4. Updated Faster R-CNN model applied to present dataset yielded an efficiency of 95.48% in detection of sugar beet leaf spot disease. As known, to apply the deep learning methods successfully, diversity of samples and the number should be large. Thus, disease might be classified more effectively. However, with the parameter changes we made in the proposed approach, similar success rates were achieved with fewer images. It is thought that the model performance will be better when the number of images is increased.

30.5 Conclusion

Early identification of plant diseases and timely interventions are of major importance for reducing crop losses. Especially in wide areas of production, the application of technological methods that are faster, practical, and eliminate the margin of human error in the diagnosis of various plant diseases, identifying the severity and change of diseases, offers very important advantages. Thus, cameras mounted on drones are a cost-effective option for capturing images covering disease areas. Computer vision applications, especially image processing techniques and deep learning techniques, for disease detection have great potential benefits to assure that plant protection applications are realized more effectively. The images captured during the flight of the drone can be processed with the developed algorithms to identify diseases in real-time and automatically.

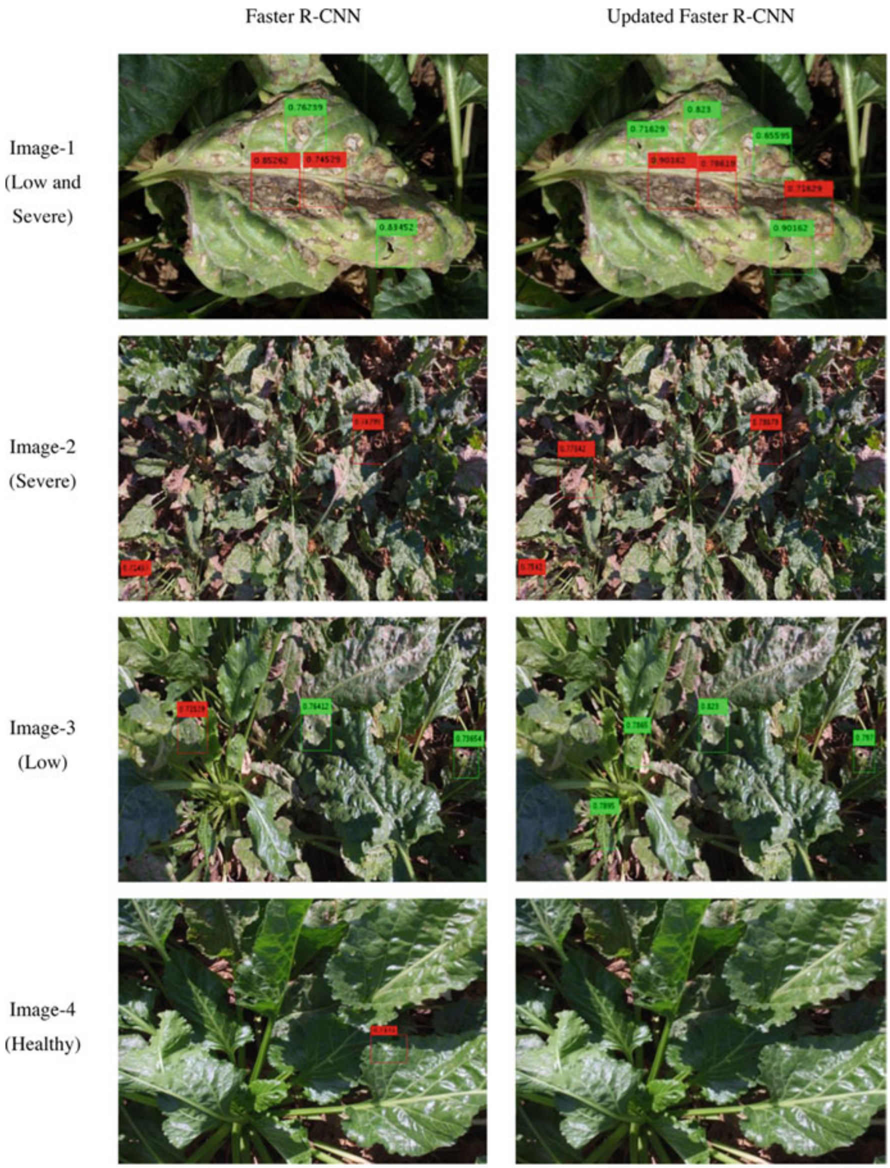

Fig. 30.9 Results of disease detection with deep learning techniques

Table 30.3 Confusion matrix of the updated Faster R-CNN architecture proposed in the study

		Predict			
		0 (healthy)	1 (low)	2 (severe)	3 (low and severe)
Actual	0 (healthy)	37	1	0	0
	1 (low)	0	19	1	0
	2 (severe)	0	1	33	1
	3 (low and severe)	0	1	2	59

Table 30.4 Assessment of the success of the updated Faster R-CNN architecture proposed in the study

	Sensitivity	Specificity	Accuracy
0 (healthy)	97,37	100	99,36
1 (low)	95	97,84	97,48
2 (severe)	94,28	97,6	96,87
3 (low and severe)	95,16	98,97	97,48
Overall	95,48	95,48	95,48

30.6 Future Prospect

Image processing techniques and machine learning techniques have been extensively studied over the last years for the determination of diseases in plants. There are many different diseases seen in plants. To detect these diseases promptly and correctly, methods such as image processing, K-means clustering, ANN, SVM, SR, and CNN might be used together. Platforms or robots might be improved to raise the image quality captured. So, it will contribute to the increment of model performances. As the model performance increases, the success in the determination and diagnosis of plant diseases will increase and so the suitable disease management program can be applied effectively.

In the future, it is expected that like disease detection processes, expert systems that automatically perform spraying operations without human intervention will be established. Robots and drones that will roam autonomously in the field or garden will identify diseases, then send expert system spraying drones or robots to spray the designated areas. In fact, spraying might be done at a variable rate, that is, only the diseased and damaged areas will be sprayed with pesticides to the extent necessary. In addition, drones, robots and other smart machines will be able to real-time communicate with each other and perform their tasks together in coordination, cooperation, or collaboration. In this way, working together will be possible with real-time communication, and with drones, robots, and smart machines, knowing where each other is and what they are doing.

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