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A sugar beet leaf disease classification method based on image processing and deep learning

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Abstract
Leaf spot disease, which causes 10 − 50% loss in sugar beet yield, causes great damage on the leaves. This disease physiologically appears as individual circular spots on the sugar beet leaves and over time spreads to the entire leaf, resulting in complete death of the leaf. Therefore, in our study, Faster R-CNN, SSD, VGG16, Yolov4 deep learning models were used directly, and Yolov4 deep learning model with image processing was used in a hybrid way for automatic determination of leaf spot disease on sugar beet and classification of severity. The proposed hybrid method for the diagnosis of diseases and identifying the severity were trained and tested using 1040 images, and the classification accuracy rate of the most successful method was found to be 96.47%. The proposed hybrid approach showed that the combined use of image processing and deep learning models yield more successful results than the analysis made using only deep learning models. In this way, both the time spent for the diagnosis of leaf spot disease on sugar beet will be reduced and human error will be eliminated, and the relevant pesticides will be sprayed to the plant at the right time.

Keywords Leaf spot disease · Sugar Beet · Faster RCNN · SSD · VGG16 · Yolov4

1 Introduction

The fast rising in the world population and urbanization lead to a decrease in agricultural areas and natural resources such as water per capita. Therefore, it has become necessary to use

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technological and genetic methods to increase productivity in agricultural production [44, 45]. Plant diseases cause economically important income losses in agricultural production all over the world. Leaf spot disease (*Cercospora beticola* Sacc.), which causes $10-50\%$ loss on sugar beet yield, is among the most significant sugar beet diseases [8, 40, 55, 57, 69]. The disease causes extensive damage to the leaves. The disease appears as individual circular spots on the sugar beet leaves and over time spreads to the entire leaf, resulting in complete death of the leaf [62]. One of the most important factors affecting plant productivity is plant diseases. Failure to detect and prevent plant diseases in a timely manner leads to significant decreases in plant yield and quality, resulting in significant economic losses for growers. Reliable and timely detection of diseases may significantly decrease such losses. Therefore, fast and accurate determination of plant disease types and assessment of disease severity is essential for the implementation of timely prevention and management strategies [6, 13, 16, 21, 38, 56, 67]. Traditional disease detection methods are mainly based on the farmers' own experience or the guidance of plant pathologists. Identifying diseases in this way is often time-consuming, laborious, and subjective. In addition, some situations such as physiological conditions and time of the day may lead to errors in visual assessments and result in misleading assessments [10, 11, 13, 17, 37, 38, 41, 75]. Plant disease can also be diagnosed via chemical methods, but it is destructive and requires many experiments that do not allow for real-time disease diagnosis [10]. In addition, these methods can sometimes be time consuming and costly when applied over the large fields and distant locations. For this reason, techniques such as image processing and deep learning, which enable the automatic determination of plant diseases, disease severity and progress of the disease without human error, have begun to be studied intensively [5, 49]. When plants are disease, they show visual signs in the form of colored spots of different shapes and sizes depending on the type of disease and in the form of lines seen on stems or different parts of the plants. These signs change color, shape and size as the disease progresses [47]. Thus, it is possible to automatically detect plant diseases by applying image processing and machine learning techniques on these images [14, 25, 68, 73]. A machine learning and IoT-based solution is proposed in which data collection, feature visualization and disease detection techniques are integrated to automate the detection and classification of Pearl Millet diseases [33]. However, there are many challenges to be solved in this area. These challenges are as follows: the wide variety of agricultural products and their different characteristics; they have irregular shapes; in case of working in natural conditions, the lighting cannot be kept under control; due to their small structure, the products come into contact with each other; due to their small structure, the products come into contact with each other, overlap or have various similar objects in the background [50]. In addition to these, changing lighting conditions, the complex background in the images, and distance to the target, sun reflection and shading also affect the quality of the image and these factors may negatively affect the diagnosis of the disease [37, 39, 42, 65].

Deep learning technique is a subcategory of machine learning. In machine learning, different algorithms and methods are used to analyze quantitative or categorical. Such algorithms rely on mathematical models that are able to cope with the complex model of the data to make predictions and inferences. Deep learning takes advantage of a wider set of tools hinging on abstract transformations of information stored within layers to manage the complexity of the data structure. Therefore, deep learning relies on learning from the representation of the data [61]. In deep learning technique, the relevant features are automatically extracted from images from huge amounts of labeled training data and taught how to automatically perform a task such as classification [7, 9, 28, 29, 46]. The deep learning method provides opportunities for more effective plant protection by identifying plant diseases and pests, determining damage levels, and monitoring the plant growth and development [47]. Therefore, lately, use of image processing techniques and machine learning techniques for disease detection in whole plant and or different plant parts such as leaves, stem, and fruit has been comprehensively studied by many researchers [20, 48, 71]. Abade et al. [1], in their review article, reported that they examined 121 of the studies carried out to determine plant diseases by using deep learning methods in the last 10 years. The deep learning models and algorithms used in scientific studies on the determination of plant diseases so far are as follows: Faster R-CNN, Mask R-CNN, YOLOV4, VGG, SSD, GAN, DCGAN, FCN, R-FCN, PDDNN, InceptionV4, Xception, DenseNet121, ResNet-152, UNet, SqueezeNet, AlexNet, GoogLeNet, PlantDiseaseNet Architecture, AutoEnconder. These models and algorithms have advantages and disadvantages compared to each other.

In our previous study on disease detection in sugar beet leaves, Faster R-CNN deep learning model was applied to raw images and classification process was performed [48]. The main motivation of the approach applied in this study is to make the diseased regions more prominent by first applying Luv color space transformation in the preprocessing step. In addition, it is aimed to increase the success rate in classification of disease severity by applying Faster R-CNN, Single Shot Multibox (SSD), VGG16 and Yolov4 deep learning architectures. The main contribution of this study is that it is the first study in which image processing and deep learning models are used together for disease detection and classification of severity in sugar beet leaf images.

2 Materials and methods

Object positioning, one of the most fundamental tasks in computer vision, is used for the detection of plant diseases. Currently, deep learning object detection methods are emerging endlessly. Deep neural networks could be trained in two ways. Deep neural networks can be trained in two ways. The first is to train this network with the data set by creating a new network model. The second is to use your dataset by customizing it with a pre-trained network and perform the training process. In our study, pre-trained Faster R-CNN, SSD, VGG16 and Yolov4 deep learning models were used to detect and classify diseased regions in sugar beet leaf images.

2.1 System configuration

Deep learning models require a very powerful GPU and CUDA. This study was carried out on a computer with Intel i7 6700 HQ, 16 GB RAM, Nvidia GTX 960 M hardware and MATLAB 2020a platform.

2.2 Dataset

Healthy and diseased sugar beet leaf images were collected at regular intervals during a growing period. A total of 1040 sugar beet leaf images used in the study; It consists of 252 healthy images, 248 low-level disease images, 288 severe disease images, and 252 both low and severe disease images. All images were individually labeled into 4 classes (Low, Severe, Both Low and Severe, Healthy) with support from Plant Protection experts.

2.3 Pre-processing

The classification performance was tried to be improved by applying image processing algorithms as preprocessing to the deep learning model. After applying adaptive histogram equalization to the 'v' channel image with Luv color space transformation applied as an image processing algorithm, the deep learning model was retrained. Image processing algorithm steps:

Step 1: RGB input image is read into the program with 'imread'.
Step 2: With the 'makeform()' function, the RGB input image is firstly transformed to xyz and then xyz to Luv color space with the same code.
Step 3: The 'v' channel of the Luv color space is assigned to a variable.
Step 4: Histogram equalization is performed with the 'adapthisteq' function to the 'v' channel assigned to the variable.

The histogram equalization method is used to adjust the pixel intensity values. This method increases the contrast values of parts of an image that are represented by narrow contrast values. Also, adaptive histogram equalization method is implemented to improve local contrast in each region of an image and to enhance definition of edges. In this method, the image is separated small blocks called tiles and increases the contrast of each tile so that the histogram of the output region approximately matches the particular histogram. After synchronization is complete, adapthisteq joins adjacent tiles with bilinear interpolation to eliminate artificially created borders.

2.4 Models

2.4.1 Faster R-CNN model

Faster R-CNN is a deep learning architecture used for object detection proposed by Girshick [23, 54]. This architecture consists of three parts as seen in Fig. 1.

As seen in Fig. 1, the features of the image were extracted by the filters in the convolution layer in the first part, and thus a feature map was created in a two-dimensional matrix structure. In the second part, the Region Proposition Network (RPN), which is used as a neural network, estimates the probability of similarity to the relevant object (prediction accuracy) if there are objects in the feature maps. In the third part, which is the prediction layer stage, two output layers are created by combining the classification value of the regions and the prediction accuracy rate using the Fast R-CNN network. The first output layer performs the softmax classification, while the other output layer is the regression layer that gives the detection accuracy. In this section, score predictions are made by determining the classes of the bounding boxes. The innovation brought by the Faster R-CNN model is that the RPN network can be connected directly to the layer where the feature map is located. In this way, it provides an environment for object detection in all images [30].

2.4.2 SSD-Single Shot Multibox model

Single Shot Multi-Box Detector (SSD) model is one of the fastest algorithms in this field, as it uses a single convolutional neural network to detect objects in images [35, 43]. It is used for object

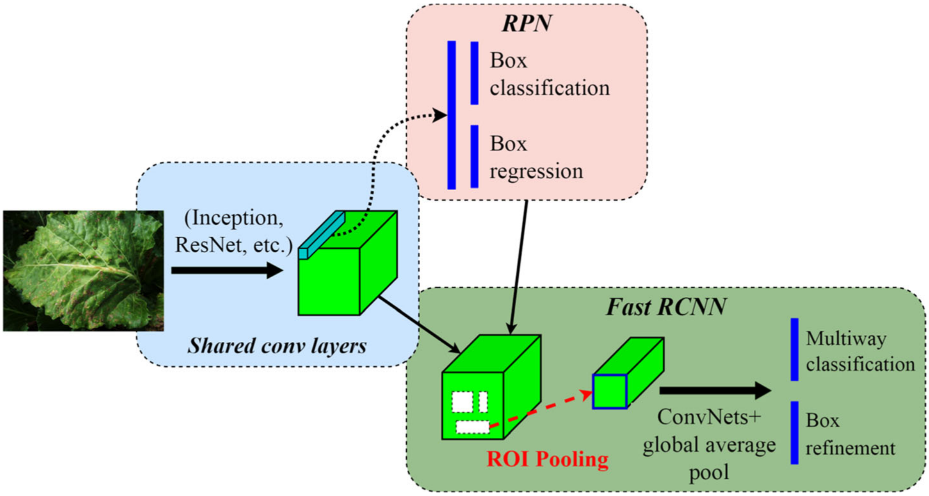

Fig. 1 Faster R-CNN architecture [53]

detection and classification on high resolution images [36]. It creates fixed size bounding boxes in the areas it has determined for object detection and calculates a prediction score for each determined box. During the training phase, all parameters in the model are updated with the back propagation algorithm and loss values [34]. In this way, the optimum filter parameters are determined and the loss value is minimized. Since it eliminates the sampling stage by performing all calculations at this stage in a single network, it is very easy and simple to implement compared to other models that perform object detection [22]. The SSD Multibox architecture is shown in Fig. 2.

2.4.3 VGG16 model

VGG16 is a CNN architecture for object detection developed by Simonyan & Zisserman from Oxford University [60]. It was developed by training in the ImageNet database [19]. It also performs well in low-dimensional image databases [51]. The VGG16 model consists of 16 convolutional layers with 3 × 3 filters and 5 Max-pooling layers with 2 × 2 filters. After the max-pooling layer, there are three fully-connected layers. ReLu activation is applied after the convolution layers. Finally, the related object and its probability are determined using the softmax classifier [24]. Figure 3 shows the VGG16 architecture.

2.4.4 Yolov4

Yolo deep learning model, which performs real-time object detection and can detect many objects in a frame, was developed by Redmon [52]. There are current and advanced versions such as Yolov2, Yolov3 and Yolov4. The Yolov4 model has been developed to achieve object detection by capturing 10% higher accuracy and 12% more frames than Yolov3 [12]. The Yolov4 architecture is as in Fig. 4.

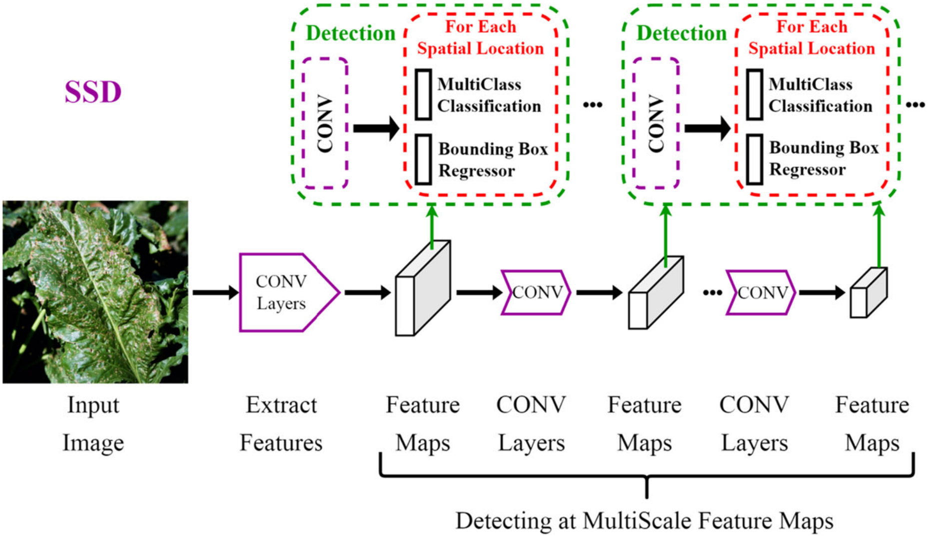

Fig. 2 SSD architecture [22]

Unlike the Faster R-CNN model, Yolov4 model does not require possible areas to be found when performing object detection [3]. Instead of processing the image separately for each object class, the image is viewed only once and box boundaries and estimation accuracies for all object classes are created. It does not require retraining for each object class. In this way, the detection of objects is performed very quickly compared to other deep learning models [70].

3 Experimental results and discussion

The performances of pretrained Faster RCNN, SSD, VGG16 and Yolov4 deep learning models were compared for the identification and classification of diseased regions on sugar beet leaf images. The classification performance was tried to be improved by applying image

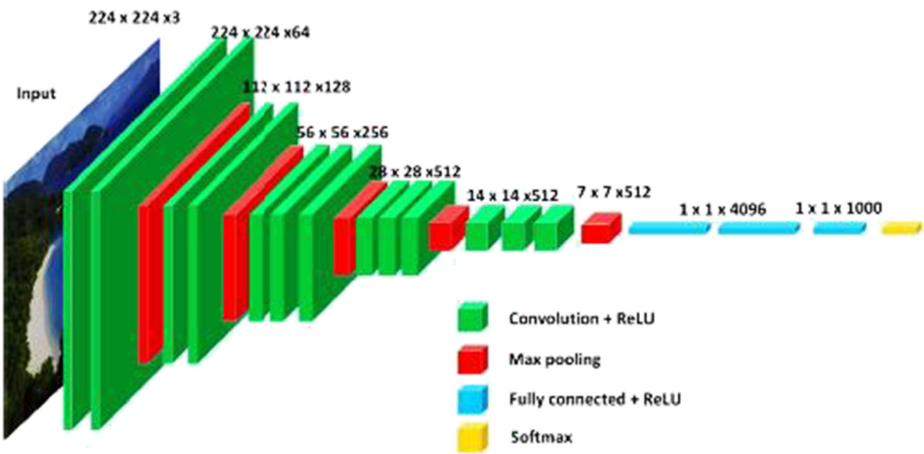

Fig. 3 VGG16 architecture [36]

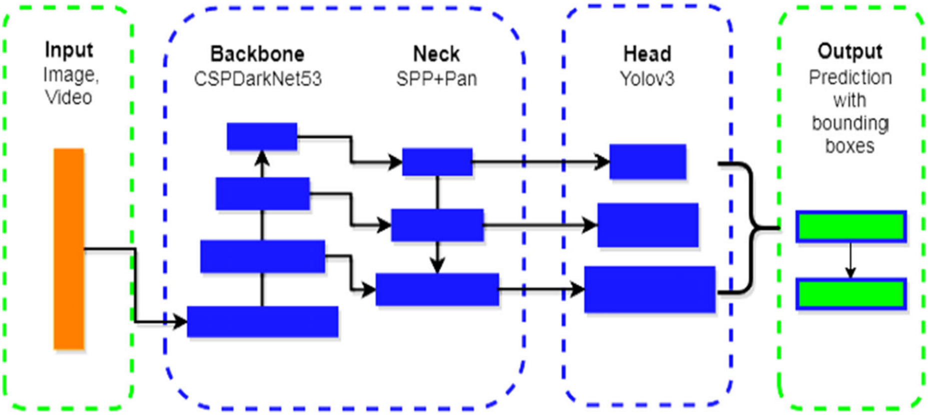

Fig. 4 Yolov4 architecture

processing algorithms as a preprocessing to the successful deep learning model. After applying adaptive histogram equalization to the '*v*' channel image with Luv color space transformation applied as an image processing algorithm, the successful deep learning model was retrained. In addition, training time performances for four deep learning models were calculated and compared. While making these calculations, all four models were run on a computer with Intel i7 6700 HQ, 16 GB RAM, Nvidia GTX 960 M hardware and MATLAB 2020a platform. A total of 1040 sugar beet leaves images were used for training and testing in deep learning models. 70% of the sugar beet leaves images (728 images) used in the experimental studies were used for training and 30% were used for testing (312 images). It is thought that the success rate for sugar beet leaf disease detection will increase due to the more numerous and variety of examples reserved for training in deep learning models [31, 48]. Also, random samples were selected from the data set for a better evaluation [72]. Table 1 shows important values regarding the deep learning models used in the study.

As seen in Table 1, based on the parameters formed during training, SSD deep learning model uses more parameters than other models. The number of parameters formed in the VGG16 model is quite high compared to other models. This situation directly affects the computational complexity of deep learning models. In addition to the computational complexity, the high classification accuracy of the model is also very important [27]. In order to perform an objective evaluation, the same values were given to the parameters during the training of the deep learning models used. The learning rate was determined at 0.001. Choosing the value too low will decrease the learning speed and increase the learning time. Choosing high causes insufficient learning because it tries to learn very quickly. The 'MiniBatchSize' value used in the weight update phase has been determined as 32. The

Table 1 Information on the deep learning models

CNN Architectures	Parameter (million)
Faster RCNN	29.1
SSD	27.2
VGG16	138.4
Yolov4	64.3

'MaxEpochs' value, which shows the number of applications of the training algorithm on the dataset, was determined as 1000. In order to prevent deep learning models from learning the diseased region with the same data, the value of 'Shuffle' was chosen as 'every-epoch'. In order to prevent over-fitting, the 'Dropout' value was set as 0.1. In the study, the processing steps of the model used for the identification of diseased regions in sugar beet leaf images and the classification of their levels are shown in Fig. 5.

As seen in Fig. 5, Faster RCNN, SSD, VGG16 and Yolov4 deep learning models, which are known for their high success detection, were applied separately to sugar beet leaf images. The reason for using Faster RCNN, SSD, VGG16 and Yolov4 models as deep learning models is accuracy and time performance [66]. As a result of the direct application of deep learning models, the most successful classification was carried out with the Yolov4 deep learning model. It was decided to apply image processing algorithms as a preprocessing step before training the images in the deep learning model in order to minimize the effects of the brightness and shadow situation caused by sunlight on the images taken in the field environment and to increase the classification success performance of the deep learning models. As a result of the experimental studies carried out as an image processing algorithm, after applying Luv color space transformation to the images, the image in the Luv color space was transferred to the *'v'* channel. Then, adaptive histogram equalization algorithm was applied to the image in the *'v'* channel and the negative effects of sunlight on the images were minimized. Sugar beet leaf images with image processing steps were retrained with the Yolov4 deep learning model, which was more successful than other models as a result of our experimental studies. Confusion matrix obtained as a result of applying deep learning models to sugar beet leaf images are given in Tables 2, 3, 4 and 5.

As can be seen in Tables 2, 3, 4 and 5, the Yolov4 model was found to be more successful than other deep learning models with an accuracy rate of 94.23% in the classification of sugar beet leaf images. Image processing algorithms and Yolov4 deep learning were applied to the accuracy rate and the results are presented in Table 6.

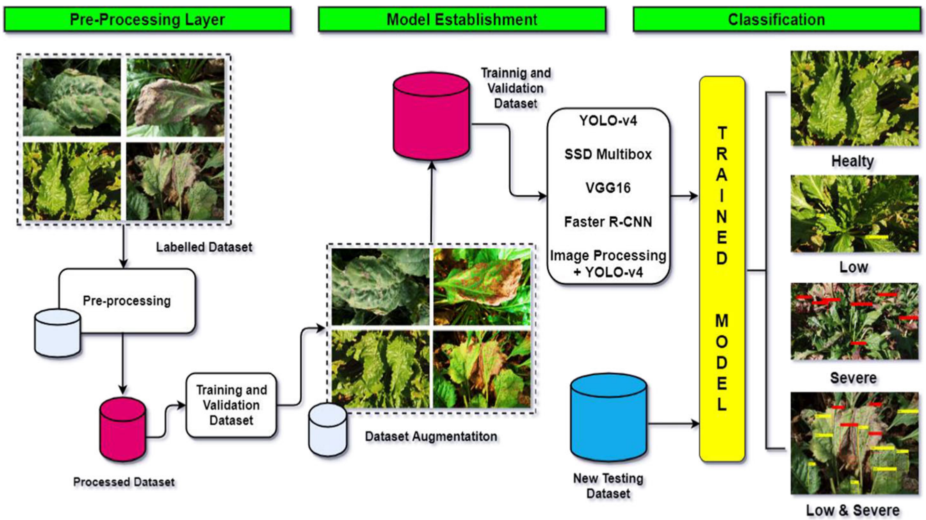

Fig. 5 General flow chart of the study

Luv color space and adaptive histogram equalization algorithms were applied as a preprocess to highlight the diseased areas in the images, and the obtained images were retrained with Yolov4 deep learning model, and the correct classification performance was increased to 96.47%. As a result of applying Yolov4 deep learning model, which is used together with image processing algorithms, 75 of 76 healthy images, 72 of 74 low-level disease images, 81 of 86 severe-level disease images, and 73 of 76 images with both low and severe diseases were correctly classified. The accuracy of the 'severe' class is lower in all models than the other classes due to the shadows and the mixing of the severely diseased areas with the background color. By enhancing the number of images compared to our previous studies, and by using the Yolov4 deep learning model together with image processing algorithms, the accuracy rate was increased to 96.47%. The Precision-Recall (PR) curve and the Roc curve are shown in Fig. 6 to better understand the results obtained as a result of using the hybrid Yolov4 model together with image processing, which is the most successful method in terms of accuracy.

The Precision-Recall (PR) curve provides a more realistic view of a model's performance when dealing with unbalanced data. As seen in Fig. 6, the data set used in our study did not have such a problem and showed consistent results. In addition, Table 7 shows the accuracy, F1 score and training time values.

As seen in Table 7, Yolov4 deep learning model used with image processing algorithms is more advantageous than other models in terms of both accurate classification performance and training time performance. The training time of the Yolov4 model is approximately one third of the training time of the Faster RCNN model. This shows that the Yolov4 model learns the same problem faster and more accurately than other models. It is expected that these methods will give faster results in training operations on higher graphics cards or TPU processors. The images obtained as a result of applying the most successful model Yolov4 and Faster R-CNN models to sample sugar beet leaf images are shown in Fig. 7.

In Fig. 7, it was seen that some diseased areas could not be detected sufficiently in the application of the Faster RCNN model. In some images, it is seen that it detects healthy areas as patients due to shadows, while in others, all diseased areas cannot be detected. It was seen that the diseased regions are detected better with the use of image processing algorithms and the Yolov4 deep learning model. This situation reveals that the Yolov4 model, which was advantageous compared to other deep learning models in the way of training time performance, was more

Table 2 Confusion matrix of the Faster RCNN model

		Predict							
		0 (Healthy)	1 (Low)	2 (**Severe**)	3 (Low & Severe)	Accuracy	Precision	Recall	F1 Score
Actual	0 Healthy	70	5	1	0	96.15	0.92	0.92	0.92
	1 Low	5	66	3	0	93.91	0.86	0.89	0.87
	2 Severe	1	5	77	3	94.23	0.90	0.90	0.90
	3 Low & Severe	0	1	5	70	97.12	0.96	0.92	0.94
Overall Accuracy						90.71			

Table 3 Confusion matrix of the VGG16 model

		Predict							
		0 (Healthy)	1 (Low)	2 (Severe)	3 (Low & Severe)	Accuracy	Precision	Recall	F1 Score
Actual	0 Healthy	68	6	2	0	95.19	0.91	0.89	0.9
	1 Low	6	64	4	0	92.63	0.83	0.86	0.85
	2 Severe	1	5	76	4	92.95	0.86	0.88	0.87
	3 Low & Severe	0	2	6	68	96.15	0.94	0.89	0.92
Overall Accuracy						88.46			

successful than the Faster RCNN model in terms of level determination and classification of diseased regions in sugar beet leaf images. The use of image processing algorithm as a preprocess has positively affected the success of the Yolov4 deep learning model. The comparison of the achievement rates of the academic studies conducted in recent years on the diagnosis of diseases in plants and the methods we recommend is given in Table 8.

In Table 8, the classification success of the models we used in the study and the results of the image processing/deep learning models used in the studies in the literature are compared. When the studies carried out in the last 3 years in the literature are examined, it is seen that deep learning models are used extensively for the diagnosis of plant diseases. It is seen that Faster RCNN, VGG16, VGG19, Yolov2 and AlexNet models are generally preferred as deep learning models in studies. In addition, it has been observed that deep learning models are applied directly to images of plant diseases in all of the studies in the literature. In this study, in order to increase the classification performance of deep learning models, image processing methods were applied to the images to make the diseased regions more prominent. As a result of applying the Yolov4 deep learning model together with the image processing algorithms to the dataset, the detection and classification of diseases in sugar beet leaves was carried out with an accuracy rate of 96.47%. It is very important for the study to increase the success rate with

Table 4 Confusion matrix of the SSD model

		Predict							
		0 (Healthy)	1 (Low)	2 (Severe)	3 (Low & Severe)	Accuracy	Precision	Recall	F1 Score
Actual	0 Healthy	71	4	1	0	96.79	0.93	0.93	0.93
	1 Low	4	67	3	0	94.55	0.87	0.91	0.89
	2 Severe	1	4	77	4	94.55	0.91	0.90	0.90
	3 Low & Severe	0	2	4	70	96.79	0.95	0.92	0.93
Overall Accuracy						91.35			

Table 5 Confusion matrix of the Yolov4 model

		Predict							
		0 (Healthy)	1 (Low)	2 (Severe)	3 (Low & Severe)	Accuracy	Precision	Recall	F1 Score
Actual	0 Healthy	73	3	0	0	97.76	0.95	0.96	0.95
	1 Low	3	69	2	0	96.15	0.91	0.93	0.92
	2 Severe	1	3	80	2	96.47	0.94	0.93	0.94
	3 Low & Severe	0	1	3	72	98.08	0.97	0.95	0.96
Overall Accuracy						94.23			

more images compared to the previous study. With this study, it is concluded that it is crucial to determine the right deep learning model for an agricultural problem. In addition, the use of image processing algorithms as preprocessing positively affects the success of the Yolov4 deep learning model. When the misclassifications are examined, it is seen that the sun-induced gleam and shadows in the images of plant leaves

4 Conclusion

In recent years, studies have been focused on the development of machine learning methods, for the automatic diagnosis of plant diseases. In these studies, it is tried to detect disease symptoms faster and to enhance the accuracy of disease classification results. As the model performance increases, the success in the identification of plant diseases will increase. In this study, it has been determined that the application of deep learning models increases the classification success, especially after preprocessing the images with image processing methods without directly giving them to the deep learning algorithms. Totally 1040 images were used for model training and testing. By applying the Yolov4 deep learning model to the

Table 6 Confusion matrix of the image processing + Yolov4 model

		Predict							
		0 (Healthy)	1 (Low)	2 (Severe)	3 (Low & Severe)	Accuracy	Precision	Recall	F1 Score
Actual	0 Healthy	75	1	0	0	99.36	0.99	0.99	0.99
	1 Low	1	72	1	0	98.08	0.95	0.97	0.96
	2 Severe	0	2	81	3	97.44	0.96	0.94	0.95
	3 Low & Severe	0	0	3	73	98.08	0.96	0.96	0.96
Overall Accuracy						96.47			

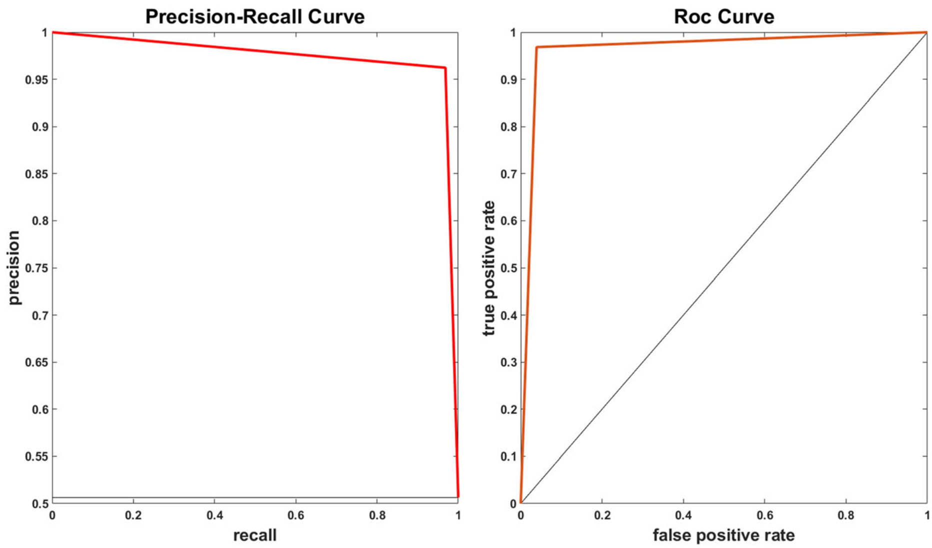

Fig. 6 PR Curve and Roc Curve of the image processing + Yolov4 model

data set with image processing algorithms, the detection and classification of diseases in sugar beet leaves was performed with an accuracy rate of 96.47%. According to this result, it was concluded that the proposed model can be used reliably in the disease detection and classification process in sugar beet leaves. To ensure the application of model development studies in large areas, it remains to establish systems that will enable these models to work in real-time conditions in the field, garden and greenhouse conditions. When the images to be entered into the model to determine the diseases are taken with the cameras mounted on the drones and real-time and automatic processing in the model is provided, identification and classification of diseases in large production areas will be provided in a short time and at affordable cost.

Advances in machine learning and imaging technologies contribute to the real-time acquisition and easier identification of plant disease images. It also allows digital images to be encrypted for rapid transfer and protection of data in pixels. In addition, researchers are working intensively on this issue. For this reason, it is expected that new models will be developed that will increase the success rates even more. However, it is important to design these studies to assist plant pathologists in improving plant disease control. Recently, many studies have been carried out by computer researchers using ready-made disease datasets. In the studies conducted without expert opinion, wrong conclusions can be reached. This is because image processing and machine learning algorithms determine the presence of disease

Table 7 Accuracy values and time performances of deep learning models

Method	Accuracy (%)	F1 Score (%)	Training Time (hours)
Faster R-CNN	90.71	0.902	12
Vgg16	88.46	0.8865	21
SSD	91.35	0.9125	133
Yolov4	94.23	0.9475	4.5
Image Processing+Yolov4	96.47	0.9625	4.5

Fig. 7 Application of deep learning models to sugar beet leaves images

based on the symptoms in the image, but it cannot associate the symptoms to its causal agent. Association is possible only with some laboratory diagnostics. In the absence of laboratory diagnosis, other similar necrotic spots could be detected in the same way, despite they can be related to other biotic or abiotic factors. This will cause the study to be inaccurate or give an incorrect assessment. An experienced plant pathologist can visually assess the symptoms and make a diagnosis also recommending further laboratory analyses.

Table 8 Comparison of studies on disease diagnosis in plant leaves

Authors	Year	Objective	Number of Image	Method		Sens.	Spec.	TCC
Agarwal et al. [4]	2020	Tomato disease	18,160	CNN		-	-	98.4
Darwish et al. [18]	2020	Maize diseases	15,408	Inception-v3		-	-	96.6
				Xception		-	-	96.5
				Ave. Ensemble model		-	-	98.2
Sharma et al. [58]	2020	Plant disease	1350	S-CNN		-	-	98.6
Shin et al. [59]	2021	Strawberry disease	11,600	ResNet 50		97.99	98.25	98.11
				GoogLeNet		96.31	96.74	96.36
				AlexNet		95.64	95.54	95.59
				SqueezeNet		95.29	96.49	95.80
				SqueezeNet-MOD1		95.84	96.30	96.38
				SqueezeNet-MOD2		93.48	92.52	92.61
Temniranrat et al. [64]	2021	Rice diseases	868	Deployment model		-	-	95.6
Zhang et al. [74]	2021	Soybean disease	2200	MF^3 R-CNN		-	-	83.34
				Yolov2				25.78
				Faster R-CNN				52.83
Hu et al. [26]	2021	Tea disease	398	Updated Faster RCNN		-	-	91.22
Yadav et al. [71]	2021	Peach disease	120	CNN+Image Processing		-	-	98.75
Sujatha et al. [63]	2021	Plant disease	609	Inception-v3		-	-	89
				VGG-16		-	-	89.5
				VGG-19		-	-	87.4
Chen et al. [15]	2020	Plant disease	500	Inception+VGGNet		-	-	91.83
Krishnamoorthy et al. [32]	2021	Rice disease	1300	Inception+ResNetV2		-	-	95.67
Abbas et al. [2]	2021	Tomato plant disease	16,012	C-GAN+DenseNet121	5 Classes	-	-	99.51
					7 Classes	-	-	98.65
					10 Classes	-	-	97.11
Ozguven and Adem [48]	2019	Sugar beet disease	155	Faster RCNN		92.89	92.89	92.89
				Updated Faster RCNN		95.48	95.48	95.48
Proposed method	2022	Sugar beet disease	1040	Faster RCNN		-	-	90.71
				VGG16		-	-	88.46
				SSD		-	-	91.35
				Yolov4		-	-	94.23
				Image Processing+Yolov4		-	-	96.47

Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Hence, the authors declare No Conflict of Interest.

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