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Detecting Wheat Leaf Diseases: A Deep Feature-Based Approach with Machine Learning Classification

Yavuz Ünal[1,*], Muzaffer Bolat[2]

[1]Amasya University, Computer Engineering Department, Amasya, Türkiye

[2]Amasya University, Technology and Innovation Management, Amasya, Türkiye

HIGHLIGHTS

- This study introduces a methodology aimed at early diagnosis of wheat leaf diseases.
- The approach relies on deep features to achieve high precision and accuracy in identifying diseases.
- Various machine learning models are employed to effectively classify wheat leaf diseases.
- The developed method ensures high accuracy rates in disease detection, contributing to increased agricultural productivity.

Abstract

Wheat is a rich storehouse of nutrients with many different vitamins and minerals. Wheat is one of the main cereals that meet the nutritional needs of humans and other living things and is used in the production of other foods. It can be grown in almost all regions of the world. It requires less irrigation compared to other plants. One of the most important problems in wheat cultivation is the fight against diseases. Wheat diseases cause yield losses and quality decreases as in other agricultural products. Timely and accurate diagnosis of these diseases; It is clear that it will lead to an increase in yield and quality. Detection of these diseases with the naked eye can be difficult and laborious. In this study, diseases on wheat leaves were detected using image processing techniques. The features of septoria and stripe rust diseases on wheat leaves were extracted using pre-trained networks VGG-16, VGG-19 and then classified with machine learning algorithms support vector machines (SVM), multi-layer perceptron (MLP), k-nearest neighbor (KNN). The results obtained were evaluated with performance criteria such as accuracy, sensitivity, specificity, precision and F1-Score. In the analysis, the features extracted with VGG-19 were classified with SVM method and the highest classification accuracy of 98.63% was achieved.

Keywords: Wheat leaf disease; Deep features; Deep learning

1. Introduction

Wheat, the most important cereal crop, is directly related to human survival and progress (Wen et al. 2023). Wheat is an annual plant species and is suitable for growing in cool climatic conditions. Variety, climatic conditions and soil characteristics affect the quality production of wheat. Wheat continues to be the most-produced cereal in the world (Atar 2017).

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Correspondence: yavuz.unal@amasya.edu.tr
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Wheat grain contains 14% protein, 14% starch and other nutrients such as fiber, vitamins, minerals and high-quality amino acids. Wheat was previously vital to the global diet due to its high nutritional value and excellent storage qualities. For modern food production, key wheat-derived resources such as wheat starch and wheat proteins are essential. Up to 20% of our daily caloric intake comes from bread and bakery products, which are essential for nutrition (Long et al. 2023).

In many countries in Asia, changes in grain quality to meet increasing wheat consumption require additional crop production. Continuous breeding efforts to improve yield and quality also face challenges (Figueroa et al. 2018).

One of the most important factors in wheat production is the quality of the wheat plant. If the seed quality decreases, the quality of wheat production also decreases. Diseases are the leading cause of poor quality (Özkan et al. 2021). Wheat rust, wheat powdery mildew, wheat scab, etc. are common diseases of wheat leaves (Wen et al. 2023).

Detection of plant diseases with the naked eye can be difficult and laborious. In recent years, many image-processing techniques have been used in the field of agriculture for disease detection. Detection and diagnosis of plant diseases using image processing techniques are very advantageous in terms of time, cost and convenience. Disease diagnosis with traditional methods used in the past causes a lot of labour and wasted time (Çetiner 2021).

Two of the diseases seen on wheat leaves and mentioned in the study are mentioned below:

Septoria disease is a disease that causes a decrease or even loss of crop production and yield in wheat. This disease, whose pathogen name is zymoseptoria tritici, reduces wheat yield by 30% to 50%. This disease, which is widespread in Turkey as in many countries, causes significant crop losses in wheat (Kilinç et al. 2021). This disease starts on the underside of the leaf and spreads to the upper part of the leaf. Symptoms appear as lesions with a light or dirty-colored center that can be clearly distinguished from the green part of the leaf. These lesions can spread to other healthy wheat leaves by spreading to areas where wind is effective. As the disease progresses, these lesions turn into spots and turn ash-colored (Mustafa 2020).

Stripe rust, or yellow rust disease, is a disease that causes a decrease in production and yield as in Septoria disease. This disease was first described in wheat by Gadd in 1777 in Europe. The pathogen causing this disease is now called P. striiformis. This disease is carried by the wind as the most important factor to every area where wheat production is carried out far away from each other, and it has been found that the spores of the disease agent can also be carried by people's belongings and clothes. The disease can be seen in climatic conditions with warm temperatures and high humidity. This disease, which is generally seen on the upper parts of the leaves, is also seen on the stems and ears of wheat. This disease, which resembles yellow-colored machine stitching, is also called line rust because it forms line-like areas on the leaves (Çat et al. 2017).

These diseases threaten wheat production and quality all over the world and also threaten countries whose economies and livelihoods depend on wheat (Figueroa et al. 2018).

1.1 Literature Review

In this section, studies on wheat leaf diseases in the literature are mentioned.

Xu et al. (2023) classified five classes with various pre-trained networks using a dataset of 7239 wheat leaf images. They used ZFnet, VGG-19, Incetion V4 and EfficientNet-B7 and their own proposed RFE-CNN models. They obtained 99.95% classification accuracy with RFE-CNN.

Cheng et al. (2023) obtained 96.4% classification accuracy with Resnet50 using a dataset of wheat leaf and spike images consisting of five classes.

Sheenam et al. (2023) classified a total of three classes of wheat leaves (healthy and two types of diseases) with an improved model of VGG19 from pre-trained networks. They improved a dataset of 1266 wheat leaf images and achieved 97.65% classification accuracy with VGG19.

El-Sayed et al. (2023) used a dataset consisting of three classes. The dataset they studied consists of 407 wheat leaf images. VGG16, VGG19 and InceptionResNetV2 were used as pre-trained networks in the analysis. They achieved 98% classification accuracy with VGG19.

A. ruby et al. (2022) used a dataset consisting of four classes. The dataset they studied consists of approximately 4,500 wheat leaf images. InceptionV3, DenseNet, ResNet50 and their own proposed ResNet50 were used as pre-trained networks in the analysis. They obtained 98.44% classification accuracy with their proposed ResNet50.

Bukhari et al. (2021) used a dataset consisting of three classes in their study. The dataset they studied consists of 310 wheat leaf images. They used three different segmentation techniques: Watershed, GrabCut and U2-Net. They segmented with U2-Net with a rate of 96.19%.

Mrinal et al. (2017) used a dataset consisting of four classes in their study. The dataset they studied is publicly available LWDCD2020 and consists of 12160 wheat leaf images. ResNet152 and VGG19 were used in the analysis. They obtained 97.81% classification accuracy with ResNet152.

Khan et al. (2022) classified wheat leaves using machine learning and deep learning methods for three classes, two disease and one healthy. They achieved 99.8% classification accuracy using a fine-tuned RFC model.

Nigam et al. (2021) classified wheat leaves using deep learning methods for two classes: healthy and Rust disease. The dataset consists of 2,000 wheat leaf images. They obtained 97.37% classification accuracy using CNN in the analysis.

Long et al. (2023) used a dataset consisting of five classes, four diseased and healthy. They used 999 wheat leaf images in the dataset. MobileNet, InceptionV3, VGG16, Xception and CerealConv were used in the analysis. They obtained 97.05% classification accuracy with CerealConv.

Catal Reis & Turk (2024) classified three classes, two diseased and one healthy, using deep learning methods. They used 2400 wheat leaf images in the dataset. Thirteen models such as EfficientNetB2, MobileNet, Xception, NASNetMobile, InceptionV3, DenseNet121, DenseNet169, DenseNet201, RegNetY080, ResNet50V2, ResNet101V2, ResNetRS50 and ResNetRS101 were used for classification. With the proposed method, 99.72% classification accuracy was obtained in the analysis performed by using IDLF and EL model together.

Table 1. Summary of the literature review

Description of The Problem	Class	Methods	Accuracy	References
Wheat Leaf	5	RFE-CNN	99.95%	(Xu et al., 2023)
	5	ResNet50	96.4%	(Cheng et al., 2023)
	3	VGG19	97.65%	(Sheenam et al., 2023)
	3	VGG19	98%	(El-Sayed et al., 2023)
	4	Resnet50	%98,44	(A et al., 2022)
	3	U2-Net	%96.19	(Bukhari et al., 2021)
	4	ResNet152	%97.81	(Mrinal et al., 2017)
	3	Fine-tuned RFC model	%99.8	(Khan et al., 2022)
	2	CNN	%97.37	(Nigam et al., 2021)
	5	CerealConv	%97.05	(Long et al., 2023)
	3	IDLF ve EL	%99.72	(Catal Reis & Turk, 2024)
	2	VGG16 + SVM	98.63%	Our Study

Table 1 shows that different methods have been applied to detect wheat leaf diseases on different datasets and different class numbers. Our study can be considered as unique in this field.

2. Materials and Methods

This section of the paper provides theoretical information about the dataset used, feature extractors and classifiers, and performance metrics.

2.1. Dataset

A dataset of wheat leaf images was used in the study (Getachew 2021). This dataset consists of three categories: healthy wheat, septoria and stripe rust. The number of data in the original version of this dataset and our preprocessed version are given in Table 2. The original dataset contains 407 wheat leaf images, 102 healthy, 97 septoria diseased and 208 stripe rust diseased. The images are in JPG format and have a high resolution of 4000x6000 or 6000x4000.

Table 2. Data features and explanations for dataset

Image Types	Class, Image Count	Total
Wheat Leaf (Orginal)	Healthy=102, Septoria = 97, Stripe Rust=208	407
Wheat Leaf (Pre-processing)	Healthy =78, Septoria =97, Stripe Rust=181	356

The original version of this dataset was captured with high resolution in an uncontrolled environment. The original wheat leaf images are shown in Figure 1.

Figure 1. Sample images in the dataset (a) Healthy (b) Stripe rust (c) Septoria

Many of the images in the dataset have unnecessary areas as background images. For this reason, in this study we manually removed the backgrounds from the original images. The reason for removing the backgrounds is that these parts are unnecessary and have a negative impact on the classification success. Figure 2 shows the images with background removed. The reorganized dataset contains a total of 356 wheat leaf images, 78 healthy, 97 septoria diseased and 181 stripe rust diseased.

Figure 2. Examples of (a) Healthy (b) Stripe rust (c) Septoria pictures with cleaned backgrounds

In addition, some of the pictures in the original data set were not included in the analysis because the background was not removed. Therefore, the number of images in the original dataset is different from the number of images in this study.

The flowchart of the study is given in Figure 3. First, the images in the original dataset were preprocessed and unnecessary backgrounds were removed. Then, features are extracted with the help of VGG-16 and VGG-19 pre-trained networks and classified with SVM, MLP and KNN machine learning algorithms.

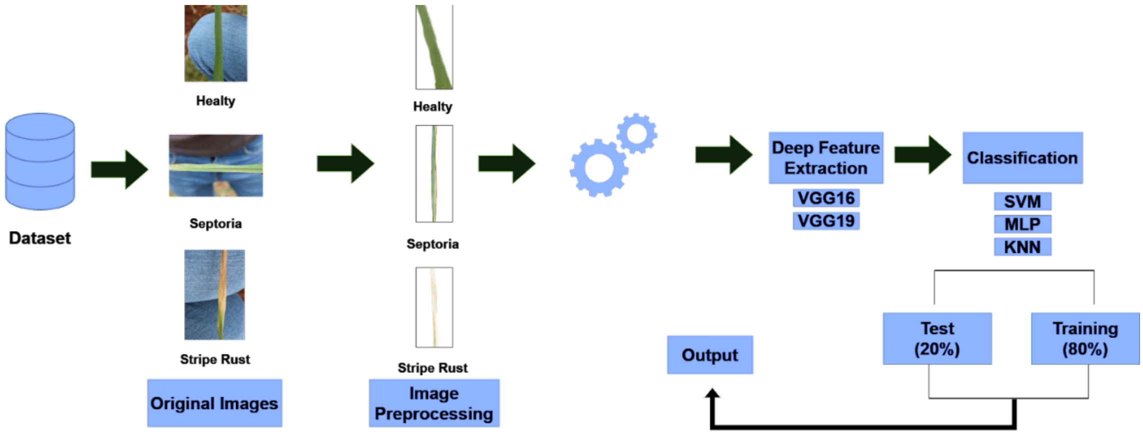


Figure 3. Graphical abstract of the study

Today, deep learning is seen as a sub-branch of artificial intelligence. Artificial intelligence started to become popular again in the early 2010s after losing interest during the so-called winter of artificial intelligence. One of the most important reasons for this interest is CNN models, which perform extremely well.

A pre-trained network, also known as a pre-trained network, is a deep learning model that has been pre-trained on large and complex data sets. Such models usually include learned weights that extract general features by learning examples from a large dataset (Dikici et al. 2022).

Deep learning techniques are not without their drawbacks. These deep learning techniques require a lot of data during the model's training (Avuçlu 2023). In situations when there is a shortage of data and computer power, transfer learning can also enhance classification performance (Goyal et al. 2021).

In this study, VGG-16 and VGG-19 pre-trained CNN models are used to extract features from wheat images. The theoretical descriptions of these models are given below.

2.2. VGG-16

VGG-16 is simple in terms of network model structure, but the most significant difference from previous models is that it is possible to use convolution layers in pairs or triples. This feature extraction model is transformed into a feature vector with 4096 neurons in the full connectivity layer. This model is a 16-layer model with approximately 138 million parameters. As we move from input to output, the width and height of the matrices decrease while the depth, i.e. the number of channels, increases (Gao et al. 2023).

2.3. VGG-19

VGG-19 is an improved model following VGG-16 and consists of 16 convolutional, 5 pooling, and 3 fully connected main layers. In other words, this feature extraction model consists of 24 main layers in total. Since VGG-19 has an in-depth network, the filters used in the convolutional layer are used to reduce the number of parameters. The size of each filter selected in this architecture is 3×3 pixels. The VGG-19 architecture has more parameters than the VGG-16 architecture and contains approximately 144 million parameters (Toğaçar et al., 2020).

2.4. SVM

Support vector machines (SVM) were developed by Vapnik et al. It is a learning method proposed by Vapnik for solving classification and curve-fitting problems based on statistical learning methodology and the principle of minimizing structural risk. This learning model belongs to the supervised learning model. SVM is divided into 3 main parts: linear separation, complete nonlinear separation, and nonlinear separation.

Recently, within the framework of statistical learning theory, Support Vector Machines (SVM) were developed and successfully used in numerous applications, from biological data processing for medical diagnosis to facial recognition and time series prediction (Karagül 2014).

2.5. MLP

In Multi-layer Perceptron (MLP), that is, Multi-layer Feed Forward Artificial Neural Networks, neurons are organized in layers. It consists of three layers: Input, Output and Hidden. The part between the Input and Output layers is called the Hidden layer. These networks can have more than one hidden layer. The processing units in the layers are interconnected. In MLP, the information analyzed by the input layer is imported into the system and the information processed by the output layer is exported. MLP emerged as a result of studies to solve the XOR problem. MLP works especially effectively in classification and generalization (Sarkar et al. 2023).

MLP is widely used as a supervised learning method or classifier in classification and regression applications in many areas such as pattern, voice recognition, classification problems. It works better on data that cannot be linearly separated. In general, it has superior performance in classification, prediction, recognition and interpretation (Erdem and Bozkurt 2021).

2.6. KNN

The K-Nearest Neighbor technique, also known as KNN, is a supervised machine learning technique that is mostly used for classification and regression issues in artificial intelligence. It is widely used for disease prediction. In general, the KNN algorithm can classify datasets using a training model similar to the test query by considering the k closest training data points (neighbors) that are closest to the query it is testing. In other words, in KNN-based classification, the distances between the test examples and the training examples are calculated and the K closest examples are selected. Among all machine learning algorithms, the KNN algorithm is one of the simplest forms and is widely used in classification applications because it has a design that is easy to implement and understand (Takci 2022).

2.7. Performance Metrics

In this section, benchmarking studies were carried out to analyze the classification performance of the pre-trained networks in the diagnosis of wheat leaf diseases. For this purpose, evaluation criteria such as accuracy, precision, recall and F1-Score were obtained with the help of confusion matrix. Accuracy is the ratio of the number of correctly predicted samples to the total number of samples in the dataset. Precision is the ratio of the number of correctly predicted diseased samples to the total number of samples predicted as diseased. Recall is a performance measure that expresses the ratio of true positives to total true positives and false negatives of a class. F1-Score is the weighted average of the sensitivity and precision parameters. It is preferred if the samples that make up the data set are unevenly distributed. These evaluation criteria can be expressed in the following formulas (Dikici et al. 2022).

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$\mathrm{F1} - \mathrm{Score} = 2 * \frac{\mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{4}$$

3. Results

Experimental studies were carried out on the COLAB platform using a workstation with Intel ® Xeon (R) 2.20 GHz CPU, NVIDIA Tesla T4 16 GB GDDR6 GPU and 16 GB ram memory. The dataset used in the study includes 78, 181 and 97 images from samples classified as healthy, stripe rust and septoria, respectively.

Tablo 3. Hyperparameters of VGG-16 and VGG-19

Input size	224x224
Minibatch size	32
Max epoch	50
Learning rate	1e-5
Optimizer	Adam

Table 3 shows that the input size of VGG-16 and VGG-19 is 224x224, mini batch size is 32, max epoch is 50, learning rate is 1e-5 and optimized as 'man'. The parameters of SVM, one of the models used for classification in this study, are given in Table 4.

Table 4. Parameters of SVM

C	10
Kernel	rbf
gamma	0.0001

For SVM, C value was chosen as 10, kernel rbf and gamma value as 0.0001. The parameters of MLP, one of the models used for classification in this study, are given in Table 5.

Table 5. Parameters of MLP

Learning Rate	0.9
Momentum	0.7
Activation function	Sigmoid

For MLP, learning rate is 0.9, momentum is 0.7 and activation function is sigmoid. The parameters of the KNN model used for classification are given in Table 6.

Table 6. Parameters of KNN

K	2
Distance Metrics	Euclidean

The confusion matrices obtained from the experimental studies are presented separately for each model in Figure 4, Figure 5. In addition, the numerical values of the performance evaluation criteria are given in Table 7. As can be seen from Table 7, after feature extraction with VGG-19, SVM classification gives the best results in all performance criteria. The average accuracy, precision, recall, and F1-score of SVM classification are 98.63%, 0.98%, 0.98%, and 0.98% respectively. The second best results are obtained by MLP classification of the features extracted with VGG-19 and SVM classification of the features extracted with VGG-16. Accuracy is 95.89%, precision is 0.96, recall is 0.95, and F1-score is 0.95. SVM gave high classification accuracy for both feature extractions. MLP showed the second-best performance in the other classes as well. In this experimental study, KNN showed the lowest classification results in all performance evaluation criteria. The average accuracy, precision, recall and F1-score of KNN are 82.19%, 0.85%, 0.82% and 0.80% for VGG-16, respectively.

Table 7. Classification results of models with KNN, MLP and SVM using feature selection methods.

Feature Extractor	**VGG-16**			**VGG-19**		
	KNN	**MLP**	**SVM**	**KNN**	**MLP**	**SVM**
Accuracy	82.19%	94.52%	95.89%	79.45%	95.89%	98.63%
Precision	0.85	0.95	0.96	0.83	0.96	0.98
Recall	0.82	0.94	0.95	0.79	0.95	0.98
F1-Score	0.80	0.94	0.95	0.78	0.95	0.98

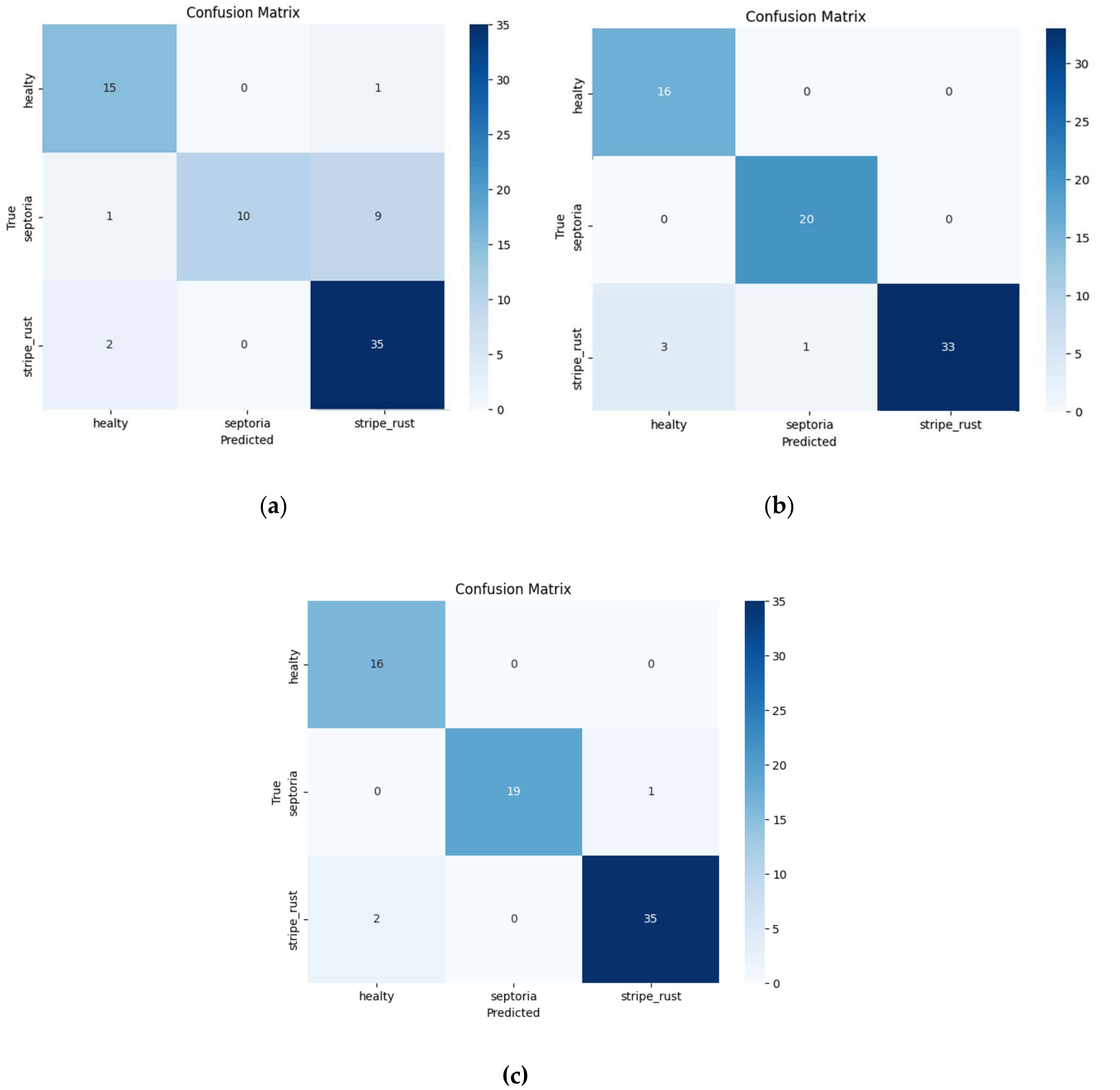
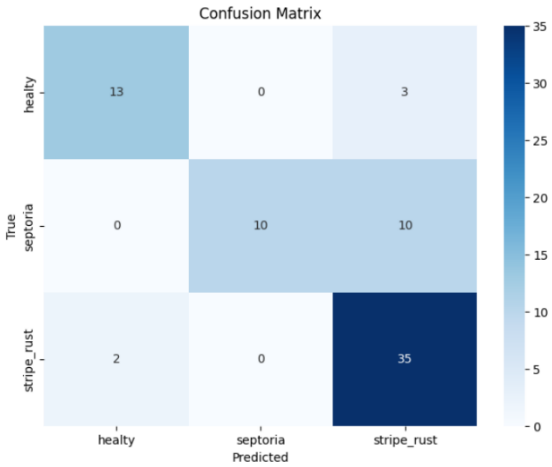
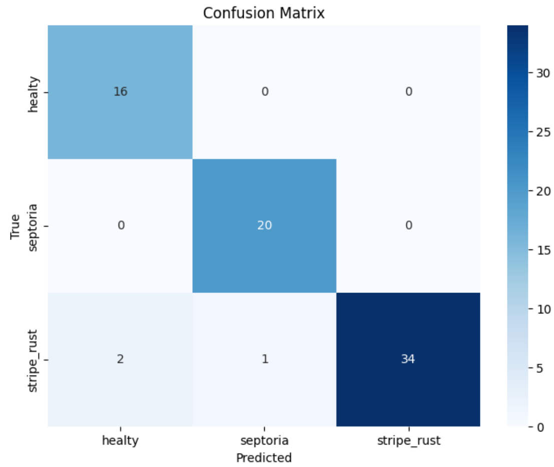


Figure 4. Confusion matrix as: (**a**) KNN with VGG-16; (**b**) MLP with VGG-16; (**c**) SVM with VGG-16

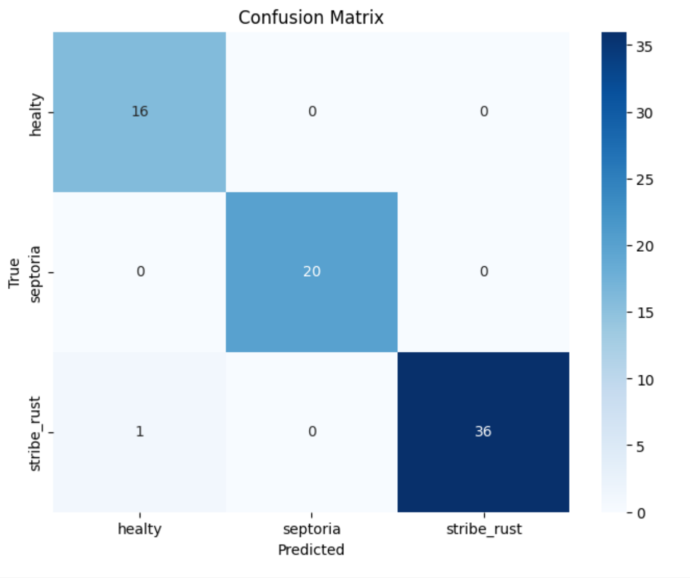
Figure 4 shows the Confusion matrices for all three classifiers (KNN, MLP, SVM) according to the features extracted with VGG-16. The number of correctly classified and misclassified instances is shown here.



(**a**)



(**b**)



(c)

Figure 5. Confusion matrix as: (**a**) KNN with VGG-19; (**b**) MLP with VGG-19; (**c**) SVM with VGG-19

Figure 5 shows the confusion matrices for the features extracted with VGG-19 for all three classifiers (KNN, MLP, SVM).

4. Discussion

In this study, two diseases seen in wheat leaves and healthy leaves were classified with image processing and machine learning. The difference of this study from other studies in the literature is that deep feature extraction and classification with machine learning algorithms KNN, MLP, SVM were performed for the first time in this study. Classification was previously performed on this dataset with pre-trained networks. In this study, differently, feature extraction was performed with pre-trained networks and classification was performed with machine learning models. Considering the classification results, high classification accuracy was obtained for this dataset. In future studies, different feature extraction methods other than VGG-16 and VGG-19 can be tested. Also, different classification models can be realized.

5. Conclusions

One of the most significant plants used as a food source worldwide is wheat. In addition to being indispensable for humans and animals, it is a plant that is easy to grow and widely cultivated all over the world (Wen et al. 2023). As in other plants, it causes significant yield and quality loss in case of disease. The most common diseases are septoria and stripe rust. Detection and diagnosis of these diseases by manual and traditional methods cause loss of time and cost. In this study, a computer-aided image processing model is proposed to classify these two diseases in wheat leaves and healthy leaves. For this purpose, a dataset of wheat leaf images was used. The backgrounds of the images were first removed. The features of the images were extracted from the pre-trained networks VGG16 and VGG19. These extracted features were classified with three different machine learning models. In the analysis, the highest classification accuracy was obtained with 98.63% when the features extracted with VGG19 were classified with SVM. It was seen that the diseases seen in wheat leaves can be successfully classified with the help of image processing and machine learning. Image processing and machine learning can be successfully used in agricultural fields. Different models can be used to improve classification performance in subsequent research. Additionally, creating various hybrid models can lead to improved categorization outcomes.

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