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Analysis of Potato Diseases Using Image Processing Methods for Detection

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ABSTRACT

Potatoes are one of the basic food sources consumed by living organisms. Potatoes are naturally vulnerable to diseases. Potatoes are a food that can spoil over time, and their nutritional value gradually decreases during this process. Therefore, the quality of potatoes needs to be continuously monitored during the production phase. For this reason, image processing tools are now being used to detect potato diseases. Based on this motivation, this study uses data from 451 different potato images. This dataset contains 7 disease classes: Black Scurf, Blackleg, Common Scab, Dry Rot, Healthy Potatoes, Miscellaneous, and Pink Rot. Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Logistic Regression (LR) methods were used for the classification of this data. Confusion matrix and accuracy, precision, recall, and F1 Score metrics were used to analyze the classification success of the models. As a result of training and testing the models, classification success rates of 68.5% were achieved with the ANN model, 54.8% with the KNN model, 65.6% with the SVM model, and 67.0% with the LR model. The highest classification success was obtained from the ANN model. In conclusion, it can be said that all classification models can be used to detect potato diseases.

1. Introduction

Advances in technology have significantly shaped agricultural policy. Particularly with the widespread use of sensor-based data collection and automation systems, the detection and quality control of potato diseases have become more systematically monitored. This is of great importance both for increasing production efficiency and for protecting the harvested potatoes. Today, many farms use smart seeding systems, and these systems provide continuous data on the health status of the plants. While these data are analyzed in conjunction with components such as emerging early changes or yield estimations, the identification of these components has also become increasingly important. Potatoes are a staple food in human nutrition, ideal for their fat, protein, and mineral content. However, these values can vary depending on irrigation methods and the minerals and systems used in storage. Therefore, regular monitoring of potato production is necessary for both the sustainability and health of production. This capability is achieved through the use of data analysis and machine learning methods; visual data obtained from potato samples makes it possible to visualize their quality. In recent years, the use of machine learning-based models has significantly increased accuracy rates in food distribution quality control and expansion. These methods minimize human-induced evaluation errors by automatically extracting meaningful features from the obtained data, making the analysis process faster and more reliable. Many studies have been conducted in the literature regarding the identification of potato diseases. Some of these sections are listed below.

In one study, Arshaghi et al. used a data archive of 5000 images from the CFIA and USDA databases to detect diseases in potatoes using the Convolution Neural Network (CNN) method. They achieved 100%

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classification success using the CNN method. They contributed to the literature by demonstrating that potato diseases can be identified using a different image processing method [1].

In one study, Singh and Kaur used Plant Village Dataset data to identify diseases on potato leaves using the K-Means Methodology. They achieved an accuracy rate of 95.99% using the K-Means Methodology. Their work contributed to the literature on the detection of diseases on potato leaves [2].

In another study, Oishi et al. used data from images taken in Sapporo and Obihiro regions of Japan in June-July 2019 and 2020 to identify healthy or diseased potatoes using the Variational Autoencoder (VAE) method. They achieved an accuracy rate of 96.7% with the VAE method. Their work contributed to the literature on identifying potato diseases using portable cameras with the VAE method [3].

In yet another study, Alzakari et al. used Potato Leaf Disease Based on Weather Details data to identify diseases on potato leaves using Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) methods. They achieved 97.1% success rates with CNN-LSTM methods. They contributed to the literature by using CNN-LSTM methods in image processing and agricultural activities [4].

In one study, Zhang et al. used data from their own experiments to investigate early intervention for early blight disease in potato leaves using CNN and Multiple Scattering Correction (CNN-MSC), CNN and Wavelet Transform (CNN-WT), CNN and First-Order Difference (CNN-D1), and CNN and Second-Order Difference (CNN-D2) methods. They achieved 100% success rates with CNN-WT and CNN-D2 methods. They contributed to the literature by using hyperspectral imaging technology to detect crop pests and prevent the spread of this disease [5].

In one study, Kumar and Patel used the Hierarchical Deep Learning Convolutional Neural Network (HDLCNN) method to first extract leaf characteristics, then identify leaf diseases, and finally perform proactive interventions on diseased plants using data from the Kaggle The Plant Village Dataset. The HDLCNN method yielded 16% more successful results than other methods. They have contributed to the literature by using the HDLCNN method for disease detection and categorization [6].

In one study, Anim-Ayeko et al. developed a model using The Plant Village Dataset data with the ResNet-9 method, considering leaf shape, existing diseases, and the overall green area of the leaf... They achieved an overall success rate of 99.33% with the ResNet-9 method. They contributed to the literature by providing image analysis and image processing using ResNet-9 [7].

In another study, Baron et al. used data consisting of photographs they had taken themselves to identify plant diseases using Support Vector Machine (SVM) and CNN methods, and compared these two methods. They achieved a success rate of 97% with the CNN method and 87% with the SVM method. They contributed to the literature by enabling farmers to produce more productive crops and detect diseased crops early using these methods [8].

In yet another study, Tarık et al. Using data from The Plant Village Dataset, they performed a procedure to identify diseases in potato leaves using the CNN method. They achieved a 99% success rate with the CNN method. They have contributed to the literature by using CNN methods to detect diseases and animal attacks on potato leaves [9].

In one study, Bienkowski et al. used their own data to detect late blight and black leg diseases on potatoes using Partial Least Squares (PLS) and Backpropagation Neural Network (BPNN) methods. They achieved a 76% success rate with PLS and BPNN methods. They have contributed to the literature by using PLS and BPNN methods for early diagnosis of plant diseases through image processing [10].

In one study, Kadam et al. (2022) performed automated disease detection using machine learning and image processing techniques with 2034 potato leaf images. They achieved results with 94% accuracy using support vector machines and decision tree methods. They developed a mobile-based diagnostic device. It has been used in the field of rapid field diagnostic systems. They have contributed to the literature by providing mobile solutions that enable farmers to diagnose diseases instantly in the field [11].

In one study, Iqbal and Talukder (2020) performed automatic diagnosis of potato leaf diseases using image segmentation and machine learning with 450 images from the PlantVillage dataset. They achieved an accuracy rate of 97% using the Random Forest algorithm method. They developed an automatic classification software. It has been used in the field of artificial intelligence-supported decision systems in agriculture. They have contributed to the literature by reducing yield loss through early diagnosis of diseases [12].

In another study, Islam et al. (2017) performed disease classification using image segmentation and a multi-class support vector machine with 300 potato leaf images. They achieved an accuracy rate of 95% using the SVM algorithm method. They developed a plant health monitoring system. It has been used in the field of food safety and sustainable agriculture. They have contributed to the literature by increasing the accuracy of agricultural diagnostic systems through image processing [13].

In yet another study, Pinki et al. performed disease diagnosis using rice leaf disease data with K-means clustering and SVM methods. They achieved a great success rate of 92.06% accuracy using the SVM method. They developed a visual content-based diagnostic device.

It has been used in methods such as diagnosing cereal diseases. They have contributed to the literature with systems based on visual feature extraction [14].

In one study, Faria et al. performed image processing and classification operations with Hybrid Deep Learning methods using potato disease data consisting of 451 images verified by the Bangladesh Agricultural Research Institute. They achieved a 97% accuracy rate with the Random Forest algorithm, one of the machine learning methods. They developed an automated disease diagnosis device. They made contributions to the literature such as AI-assisted disease diagnosis in digital agriculture applications [15].

According to research in the literature, the contributions of this study can be listed as follows:

• In the study, features with high representational power were extracted from images of potato diseases with low computational cost using SqueezeNet, one of the deep learning architectures. This can contribute to the development of efficient agricultural systems, especially in environments where financial resources are limited and sufficient equipment is lacking.

• Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Logistic Regression (LR) algorithms were applied to the obtained features, and the performance, accuracy, and generalization capabilities of different classification approaches were systematically compared. This comparison reveals the potential of integrating classical machine learning methods with deep features.

• In this study, multi-class diagnosis performance was evaluated using a seven-class potato disease dataset consisting of 451 images. In this respect, it goes beyond the generally two-class (diseased/normal) models in the literature and demonstrates the effectiveness of deep features in more complex classification scenarios.

• The proposed method, using a combination of transfer learning and classical machine learning models, has achieved both high accuracy and interpretability. This integrated approach offers a viable and rapid alternative for detecting diseased potatoes in potato production fields.

The rest of the article is structured as follows: Section 2, Materials and Methods, presents the dataset used in the study, the methods employed, and performance metrics. Section 3 includes the experimental results and discussions from the study. Section 4 presents the study's conclusions, contributions, limitations, and application areas.

2. MATERIAL AND METHODS

2.1. Potato Diseases Datasets (PDD)

The dataset used in the study contains a total of 451 images in 7 classes. The classes are Black Scurf, Blackleg, Common Scab, Dry Rot, Healthy Potatoes, Miscellaneous, and Pink Rot. There are 58 images in the Black Scurf class, 60 in the Blackleg class, 62 in the Common Scab class, 60 in the Dry Rot class, 80 in the Healthy Potatoes class, 74 in the Miscellaneous class, and 57 in the Pink Rot class [15, 16].

Images in the Healthy Potatoes and Miscellaneous categories are 224x224 pixels in size.

The images in the Black Scurf class consist of 37 photographs with a resolution of 224×224 pixels, as well as images with dimensions of 650×497, 244×215, 900×507, 645×376, 647×398, 485×417, 171×209, 516×597, 322×157, 500×500, 206×211, 210×210, 224×256, 265×238, 225×224, 294×286, 223×271, 205×311, 250×227, and 225×225 pixels.

The images in the Blackleg class consist of 40 photographs with a resolution of 224×224 pixels, as well as images with dimensions of 468×315, 297×169, 394×450, 138×269, 650×679, 335×262, 303×202, 250×202, 400×279, 900×597, 338×253, 304×252, 481×637, 335×254, 335×253, 255×313, 1021×680, 1770×1374, 1556×1326, and 100×838 pixels.

The images in the Common Scab class consist of 47 photographs with a resolution of 224×224 pixels, as well as images with dimensions of 318×159, 183×137, 183×123, 650×457, 182×137, 280×436, 183×137, 640×480, 547×343, 300×194, 646×450, 240×200, 685×532, and 1024×674 pixels.

The images in the Dry Rot class consist of 45 photographs with a resolution of 224×224 pixels, as well as images with dimensions of 548×365, 517×327, 238×318, 427×320, 257×196, 327×262, 640×447, 220×318, 224×318, 283×178, 600×472, 426×319, 452×360, 369×365, and 1068×580 pixels.

The images in the Pink Rot class consist of 46 photographs with a resolution of 224×224 pixels, as well as images with dimensions of 896×502, 416×121, 250×251, 704×526, 350×116, 700×842, 349×220, 396×619, 156×163, 208×242, and 1181×894 pixels.

Figure 1 shows sample images from the dataset.

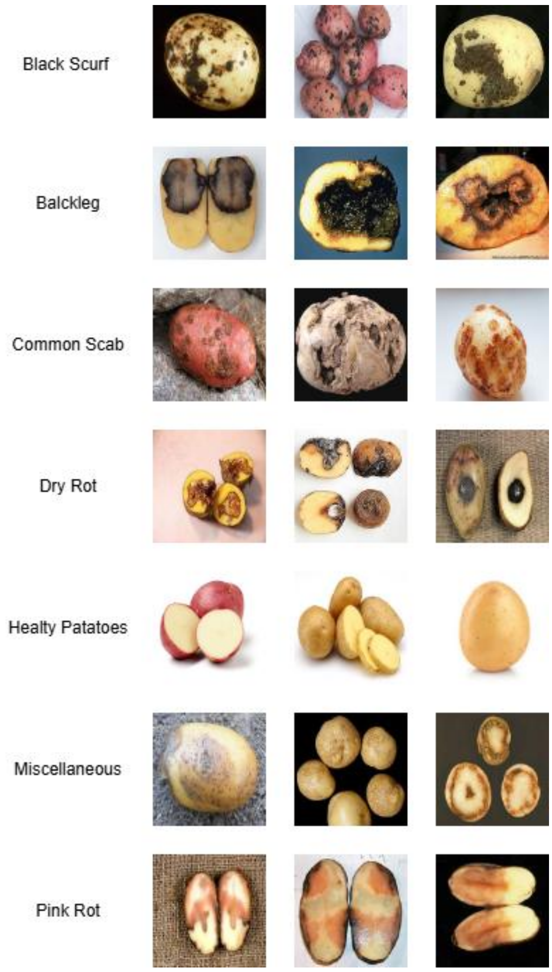

Figure 1. Shows Sample Images From The Dataset.

2.2. Convolutional Neural Networks (CNN)

Convolutional Neural Networks are one of the most important architectures of deep learning and are used especially in the processing of visual data. CNNs automatically extract features from images through filters. While simple patterns such as edges and corners are learned in the first layers, more complex structures are recognized in the deeper layers [17]. The features extracted at the end of this process are used for classification or prediction. The structure of a CNN consists of 3 layers: convolution layers, activation functions, pooling layers, and fully connected layers. Convolution layers generate feature maps, activation functions such as ReLU learn nonlinear relationships, pooling layers reduce dimensionality and increase generalization ability, and fully connected layers convert the extracted information into classification. Historically, models such as LeNet, AlexNet, VGG, and ResNet have been milestones in the development of CNNs. Today, CNNs are used in many fields such as image classification, object detection, face recognition, natural language processing, medicine, and agriculture. The advantages it provides include automatic feature extraction, high accuracy and parameter efficiency, while its disadvantages are high computational cost, the need for large datasets and interpretation difficulties [18]. As a result, CNNs are considered to be one of the cornerstones of modern artificial intelligence, providing near-human level accuracy in visual data.

2.3. SqueezeNet Architecture

SqueezeNet is a compact convolutional neural network architecture developed by Forrest Iandola and his team in 2016. While large models like AlexNet offer high accuracy with the rise of deep learning, their millions of parameters have made their use difficult in mobile devices and embedded systems. Designed as a solution to this problem, SqueezeNet offers AlexNet-level accuracy while using approximately 50 times fewer parameters and reducing the model size to below 0.5 MB [19]. The most important innovation of SqueezeNet is its Fire Module structure. This module consists of two parts: the squeeze layer and the expand layer. The first layer reduces input parameters, while the second layer increases filtering capabilities. Thus, the model maintains its capacity to learn complex features while keeping its low parameter requirements. SqueezeNet's advantages include low memory consumption, fast operation, and reduced hardware requirements. Due to its small size, it is preferred in mobile devices, IoT systems, and applications requiring energy efficiency. It is also quite suitable for transfer learning [20]; it can be easily retrained for different tasks. However, larger and more complex architectures such as ResNet or EfficientNet can provide higher accuracy in some tasks [21]. SqueezeNet has demonstrated the applicability of deep learning in mobile and embedded systems with its lightweight but powerful structure. SqueezeNet was chosen for feature extraction from images because its architecture can generate deep features with high representational power at very low computational cost. SqueezeNet achieves a similar accuracy level to AlexNet while using approximately 50 times fewer parameters, significantly reducing memory and hardware requirements. Furthermore, its transfer learning-friendly structure allows for the efficient use of 1000 deep features extracted from potato disease images in machine learning algorithms such as ANN, KNN, SVM, and LR.

2.4. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are an artificial intelligence model developed by drawing inspiration from the functioning of neurons in the human brain. They basically consist of 3 layers: input, hidden, and output layers. The input layer receives the data, the hidden layers weight this data and process it through activation functions, and the output layer produces the final prediction. The learning process is based on error calculation and updating the weights with the backpropagation algorithm. The historical development of ANNs began with McCulloch & Pitts' artificial neuron model in 1943, and learning networks emerged with Rosenblatt's perceptron in 1958 [22]. In the 1980s, the backpropagation algorithm made it possible to train multi-layer networks, and from the 2000s onwards, thanks to big data and powerful hardware, it paved the way for deep learning. Its advantages are flexibility, automatic learning, and high accuracy; The disadvantages are high computational costs, the need for large datasets, and interpretability challenges. Today, ANNs have become a powerful architecture at the heart of modern artificial intelligence, further enhanced by transfer learning and transformer-based models [23].

2.5. K-Nearest Neighbor (KNN)

K-Nearest Neighbor is one of the simplest and most understandable algorithms used in machine learning. It is among the supervised learning methods and its basic principle is based on the "similar data are close to each other" approach. It is a non-parametric and lazy learning algorithm; that is, it does not perform complex calculations during the training phase, all operations take place during prediction. The advantages of the algorithm include simplicity, flexibility, non-parametric structure, and high accuracy in small datasets. Its disadvantages are high computational cost in large datasets, memory dependence, scale sensitivity, and reduced performance in multidimensional data. KNN is used in many fields such as image processing, medicine, finance, and agriculture. Thanks to modern optimization techniques (KD-Tree, Ball-Tree, weighted KNN), it can also be used in large datasets. In conclusion, KNN is an indispensable algorithm in both academic and industrial applications with its simplicity and strong performance [24].

2.6. Support Vector Machine (SVM)

Support Vector Machine is used in supervised learning. Its main purpose is to find the hyperplane that best separates different classes in the dataset [25]. The points closest to this hyperplane are called “support vectors” and determine the decision boundary. SVM increases generalization ability by maximizing the margin between classes. Advantages of SVM include high accuracy, resilience to over-learning, and flexibility. Disadvantages include high computational cost in large datasets, critical kernel selection, and difficulty in hyperparameter tuning [26]. Its application areas are quite broad: it is successfully used in many fields such as spam filtering, sentiment analysis, bioinformatics, financial risk analysis, facial recognition, and medical diagnostics. In addition, “Support Vector Regression (SVR)” has been developed for regression problems. Among modern developments, multi-class SVM approaches (One-vs-One, One-vs-Rest), GPU-accelerated solutions, and integration with deep learning stand out [27]. In conclusion, SVM remains an important and powerful tool in both academic and industrial applications.

2.7. Logistic Regression

Logistic Regression is one of the fundamental methods widely used in statistical modeling and machine learning to solve classification problems. This approach aims to model the relationship between independent variables and categorical dependent variables and to make probability estimations. Unlike linear regression, Logistic Regression produces limited probability values in the range of 0 to 1 instead of continuous values [28]. These probabilities are modeled through logit transformation, and the coefficients are determined using the Maximum Likelihood Estimation (MLE) method. The most common form of the model is binary classification (binary logistic regression), which separates two classes [29]. However, thanks to its multinomial and ordinal versions, it can also be applied to more complex classification problems. Logistic Regression has a wide range of applications, such as disease diagnosis in healthcare, credit risk analysis in the finance sector, predicting customer behavior in marketing, and spam email detection in natural language processing. The model's advantages include interpretability, computational efficiency, and the ability to make probability estimates [30]. However, its disadvantages include its inadequacy in nonlinear relationships and its lower performance in complex datasets.

2.8. Confusion Matrix

The confusion matrix is used to evaluate the prediction performance of training and test data. The values in the matrix are commonly used for performance measurement of classification problems. The confusion matrix of a two-class classification problem in the study is shown in Figure 2. The meanings of the rows and columns are as follows.

		Real Clas	
		Positive	Negative
Prediction Class	True	TP	TN
	False	FP	FN

Figure 2. Confusion Matrices

TP: True Positive. An example where the actual representation of the model is 1 and the predicted representation is also 1.

TN: True Negative. An example where the actual representation of the model is 0 and the predicted representation is also 0.

FP: False Positive. An example where the actual representation of the model is 0 and the predicted representation is 1.

FN: False Negative. Examples where the actual representation of the model is 1 and the predicted representation is 0.

2.9. Performance Metrics

Performance determination is used to evaluate the classifier performance. In this study, true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values, as well as basic performance metrics such as accuracy, F-1 score, sensitivity, precision, and specificity, were calculated. The calculation formulas for these criteria are given below.

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

$$\frac{2TP}{2TP + FP + FN} \tag{2}$$

$$\frac{TP}{TP + FN} \tag{3}$$

$$\frac{TP}{TP + FP} \tag{4}$$

$$\frac{TN}{TN + FP} \tag{5}$$

3. EXPERIMENTAL RESULTS

In this study, ANN, KNN, SVM, and LR methods were used to classify the Potato Disease Dataset in order to detect potato diseases using image processing and machine learning methods, based on colony images obtained from potato producers during potato production. A computer with a Core i7™ 13620H 4.9 GHz processor, an NVIDIA GeForce RTX 4060 graphics card, and 64 GB of RAM was used. Python programming language was used. For the ANN method, the following parameters were used: 100 hidden layers, ReLu activation function, regularization 0.0001, number of iterations 200. For the KNN method, the following parameters were used: number of neighbors 5, metric euclidean, weight uniform. For the SVM method, the following parameters were used: cost 1, regression loss epsilon 0.1, kernel RBF, iteration 100. For the LR method, the regularization type Ridge L2 parameter was used. Training and testing were performed using the cross-validation method. In this method, the k value was set to 10. The procedures performed in the study are shown in Figure 3.

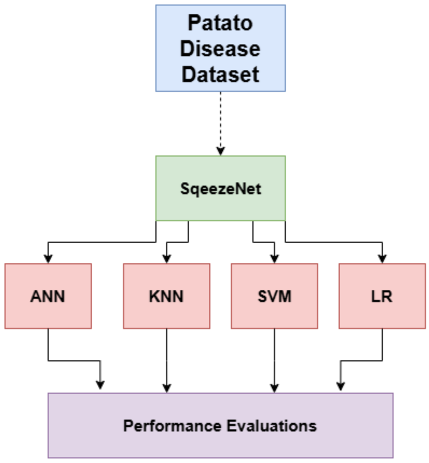

Figure 3. Flowchart

From each image obtained using the SqueezeNet architecture, 1000 features were given as input data to machine learning methods, and their training was carried out. The confusion matrices obtained from the machine learning methods are given in order. The confusion matrix obtained from the ANN method is shown in Figure 4.

		Predicted							
		Black Scurf	Blackleg	Common Scab	Dry Rot	Healty Potatoes	Miscellaneous	Pink Rot	∑
Actual	Black Scurf	44	3	6	0	1	4	0	58
	Blackleg	2	29	3	14	0	6	6	60
	Common Scab	7	0	42	4	0	7	2	62
	Dry Rot	1	12	3	36	1	4	3	60
	Healty Potates	1	0	0	1	77	1	0	80
	Miscellaneous	5	11	6	7	2	41	2	74
	Pink Rot	1	7	1	3	1	4	40	57
	∑	58	60	62	60	80	74	57	451

Figure 4. ANN Data

According to Figure 4, the ANN method correctly classified 44 data points belonging to the Black Scurf class. It classified 3 data points belonging to the Black Scurf class as Blackleg. It classified 6 data points belonging to the Black Scurf class as Common Scab. It classified 1 data point belonging to the Black Scurf class as Healthy Potatoes. It classified 4 data points belonging to the Black Scurf class as Miscellaneous. In total, it incorrectly classified 14 data points belonging to the Black Scurf class. It correctly classified 29 data points belonging to the Blackleg class. It classified 2 data points belonging to the Blackleg class as Black Scurf. It classified 3 data points belonging to the Blackleg class as Common Scab. It classified 14 data points belonging to the Blackleg class as Dry Rot. It classified 6 data points belonging to the Blackleg class as Miscellaneous. It classified 6 data points belonging to the Blackleg class as Pink Rot. In total, it incorrectly classified 31 data points belonging to the Blackleg class. It correctly classified 42 data points belonging to the Common Scab class. It classified 7 data points belonging to the Common Scab class as Black Scurf. It classified 4 data points belonging to the Common Scab class as Dry Rot. It classified 7 data points belonging to the Common Scab class as Miscellaneous. It classified 2 data points belonging to the Common Scab class as Pink Rot. In total, it incorrectly classified 20 data points belonging to the Common Scab class. It correctly classified 36 data points belonging to the Dry Rot class. It classified 1 data point belonging to the Dry Rot class as Black Scurf. It classified 12 data points belonging to the Dry Rot class as Blackleg. It classified 3 data points belonging to the Dry Rot class as Common Scab. It classified 1 data point belonging to the Dry Rot class as Healthy Potatoes. It classified 4 data points belonging to the Dry Rot class as Miscellaneous. It classified 3 data points belonging to the Dry Rot class as Pink Rot. In total, it incorrectly classified 24 data points belonging to the Dry Rot class. It correctly classified 77 data points belonging to the Healthy Potatoes class. It classified 1 data point belonging to the Healthy Potatoes class as Black Scurf. It classified 1 data point belonging to the Healthy Potatoes class as Dry Rot. It classified 1 data point belonging to the Healthy Potatoes class as Miscellaneous. In total, it incorrectly classified 3 data points belonging to the Healthy Potatoes class. It correctly classified 41 data points belonging to the Miscellaneous class. It classified 5 data points belonging to the Miscellaneous class as Black Scurf. It classified 11 data points belonging to the Miscellaneous class as Blackleg. It classified 6 data points belonging to the Miscellaneous class as Common Scab. The study incorrectly classified 7 data points belonging to the Miscellaneous class as Dry Rot. It classified 2 data points belonging to the Miscellaneous class as Healthy Potatoes. It classified 2 data points belonging to the Miscellaneous class as Pink Rot. In total, it incorrectly classified 33 data points belonging to the Miscellaneous class. It correctly classified 40 data points belonging to the Pink Rot class. It classified 1 data point belonging to the Pink Rot class as Black Scurf. It classified 7 data points belonging to the Pink Rot class as Blackleg. It classified 1 data point belonging to the Pink Rot class as Common Scab. It classified 3 data points belonging to the Pink Rot class as Dry Rot. It classified 1 data point belonging to the Pink Rot class as Healthy Potatoes. It classified 4 data points belonging to the Pink Rot class as Miscellaneous. In total, it incorrectly classified 17 data points belonging to the Pink Rot class. Figure 5 shows the confusion matrix for the KNN method.

Actual	Predicted							
	Black Scurf	Blackleg	Common Scab	Dry Rot	Healty Potatoes	Miscellaneous	Pink Rot	∑
Black Scurf	38	3	14	0	1	2	0	58
Blackleg	5	28	4	10	0	5	8	60
Common Scab	22	0	28	4	3	4	1	62
Dry Rot	4	14	12	23	2	4	1	60
Healty Potates	1	0	0	0	78	0	1	80
Miscellaneous	6	9	8	5	11	34	1	74
Pink Rot	4	10	5	7	4	9	18	57
∑	58	60	62	60	80	74	57	451

Figure 5 KNN Data

According to Figure 5, the KNN method correctly classified 38 data points belonging to the Black Scurf class. It classified 3 data points belonging to the Black Scurf class as Blackleg. It classified 14 data points belonging to the Black Scurf class as Common Scab. It classified 1 data point belonging to the Black Scurf class as Healthy Potatoes. It classified 2 data points belonging to the Black Scurf class as Miscellaneous. In total, it incorrectly classified 20 data points belonging to the Black Scurf class. It correctly classified 28 data points belonging to the Blackleg class. It classified 5 data points belonging to the Blackleg class as Black Scurf. It classified 4 data points belonging to the Blackleg class as Common Scab. It classified 10 data points belonging to the Blackleg class as Dry Rot. It classified 5 data points belonging to the Blackleg class as Miscellaneous. It classified 8 data points belonging to the Blackleg class as Pink Rot. In total, it incorrectly classified 32 data points belonging to the Blackleg class. It correctly classified 28 data points belonging to the Common Scab class. It classified 22 data points belonging to the Common Scab class as Black Scurf. It classified 4 data points belonging to the Common Scab class as Dry Rot. It classified 3 data points belonging to the Common Scab class as Healthy Potatoes. It classified 4 data points belonging to the Common Scab class as Miscellaneous. It classified 1 data point belonging to the Common Scab class as Pink Rot. In total, it incorrectly classified 34 data points belonging to the Common Scab class. It correctly classified 23 data points belonging to the Dry Rot class. It classified 4 data points belonging to the Dry Rot class as Black Scurf. It classified 14 data points belonging to the Dry Rot class as Blackleg. It classified 12 data points belonging to the Dry Rot class as Common Scab. It incorrectly classified 37 data points in the Dry Rot category. It correctly classified 78 data points in the Healthy Potatoes category. It incorrectly classified 1 data point in the Healthy Potatoes category as Black Scurf. It incorrectly classified 1 data point in the Healthy Potatoes category as Pink Rot. In total, it incorrectly classified 2 data points in the Healthy Potatoes category. It correctly classified 34 data points in the Miscellaneous category. It correctly classified 34 data points belonging to the Miscellaneous class. It classified 6 data points belonging to the Miscellaneous class as Black Scurf. It incorrectly classified 9 data points in the Miscellaneous category as Blackleg. It incorrectly classified 8 data points in the Miscellaneous category as Common Scab. The study incorrectly classified 40 data points belonging to the Miscellaneous class as Dry Rot. It correctly classified 18 data points belonging to the Pink Rot class. It classified 4 data points belonging to the Pink Rot class as Black Scurf. It classified 10 data points belonging to the Pink Rot class as Blackleg. It classified 5 data points belonging to the Pink Rot class as Common Scab. It classified 7 data points belonging to the Pink Rot class as Dry Rot. It classified 4 data points belonging to the Pink Rot class as Healthy Potatoes. It classified 9 data points belonging to the Pink Rot class as Miscellaneous. In total, it incorrectly classified 39 data points belonging to the Pink Rot class. Figure 6 shows the confusion matrix for the SVM method.

		Predicted							
		Black Scurf	Blackleg	Common Scab	Dry Rot	Healty Potatoes	Miscellaneous	Pink Rot	∑
Actual	Black Scurf	44	2	8	0	1	4	0	58
	Blackleg	2	35	3	8	0	5	7	60
	Common Scab	14	0	37	4	0	6	1	62
	Dry Rot	0	19	6	28	1	4	2	60
	Healty Potates	1	0	0	1	74	2	2	80
	Miscellaneous	5	12	6	4	3	40	4	74
	Pink Rot	1	6	0	3	1	8	38	57
	∑	58	60	62	60	80	74	57	451

Figure 6. SVM Data

According to Figure 6, the SVM method correctly classified 44 data points belonging to the Black Scurf class. It classified 2 data points belonging to the Black Scurf class as Blackleg. It classified 6 data points belonging to the Black Scurf class as Common Scab. It classified 1 data point belonging to the Black Scurf class as Healthy Potatoes. It classified 4 data points belonging to the Black Scurf class as Miscellaneous. In total, it incorrectly classified 13 data points belonging to the Black Scurf class. It correctly classified 35 data points belonging to the Blackleg class. It classified 2 data points belonging to the Blackleg class as Black Scurf. It classified 3 data points belonging to the Blackleg class as Common Scab. It classified 8 data points belonging to the Blackleg class as Dry Rot. It classified 5 data points belonging to the Blackleg class as Miscellaneous. It classified 7 data points belonging to the Blackleg class as Pink Rot. In total, it incorrectly classified 25 data points belonging to the Blackleg class. It correctly classified 37 data points belonging to the Common Scab class. It classified 14 data points belonging to the Common Scab class as Black Scurf. It classified 4 data points belonging to the Common Scab class as Dry Rot. It classified 6 data points belonging to the Common Scab class as Miscellaneous. It classified 1 data point belonging to the Common Scab class as Pink Rot. In total, it incorrectly classified 25 data points belonging to the Common Scab class. It correctly classified 28 data points belonging to the Dry Rot class. It classified 19 data points belonging to the Dry Rot class as Blackleg. It classified 6 data points belonging to the Dry Rot class as Common Scab. It classified 1 data point belonging to the Dry Rot class as Healthy Potatoes. It classified 4 data points belonging to the Dry Rot class as Miscellaneous. It misclassified 2 data points belonging to the Dry Rot class as Pink Rot. In total, it misclassified 32 data points belonging to the Dry Rot class. It correctly classified 74 data points belonging to the Healthy Potatoes class. It classified 1 data point belonging to the Healthy Potatoes class as Black Scurf. It classified 1 data point belonging to the Healthy Potatoes class as Dry Rot. It classified 2 data points belonging to the Healthy Potatoes class as Miscellaneous. It classified 2 data points belonging to the Healthy Potatoes class as Pink Rot. In total, it misclassified 6 data points belonging to the Healthy Potatoes class. It correctly classified 40 data points belonging to the Miscellaneous class. It classified 5 data points belonging to the Miscellaneous class as Black Scurf. It classified 12 data points belonging to the Miscellaneous class as Blackleg. It classified 6 data points belonging to the Miscellaneous class as Common Scab. The LR method incorrectly classified 34 data points belonging to the Miscellaneous class as Dry Rot. It also correctly classified 38 data points belonging to the Pink Rot class. In total, it incorrectly classified 34 data points belonging to the Miscellaneous class. It correctly classified 38 data points belonging to the Pink Rot class. It classified 1 data point belonging to the Pink Rot class as Black Scurf. It classified 6 data points belonging to the Pink Rot class as Blackleg. It classified 3 data points belonging to the Pink Rot class as Dry Rot. It classified 1 data point belonging to the Pink Rot class as Healthy Potatoes. In total, it incorrectly classified 19 data points belonging to the Pink Rot class. Figure 7 shows the confusion matrix for the LR method.

		Predicted							
		Black Scurf	Blackleg	Common Scab	Dry Rot	Healty Potatoes	Miscellaneous	Pink Rot	∑
Actual	Black Scurf	40	5	9	1	0	3	0	58
	Blackleg	4	28	3	9	0	10	6	60
	Common Scab	10	0	42	3	0	6	1	62
	Dry Rot	0	9	4	35	1	10	1	60
	Healty Potates	1	0	2	1	74	2	0	80
	Miscellaneous	4	9	5	8	4	40	4	74
	Pink Rot	0	5	1	3	0	5	43	57
	∑	58	60	62	60	80	74	57	451

Figure 7. LR Data

According to Figure 7, the LR method correctly classified 40 data points belonging to the Black Scurf class. It classified 5 data points belonging to the Black Scurf class as Blackleg. It classified 9 data points belonging to the Black Scurf class as Common Scab. It classified 1 data point belonging to the Black Scurf class as Dry Rot. It classified 3 data points belonging to the Black Scurf class as Miscellaneous. In total, it incorrectly classified 18 data points belonging to the Black Scurf class. It correctly classified 28 data points belonging to the Blackleg class. It classified 4 data points belonging to the Blackleg class as Black Scurf. It classified 3 data points belonging to the Blackleg class as Common Scab. It classified 9 data points belonging to the Blackleg class as Dry Rot. It classified 10 data points belonging to the Blackleg class as Miscellaneous. It classified 6 data points belonging to the Blackleg class as Pink Rot. In total, it incorrectly classified 25 data points belonging to the Blackleg class. It correctly classified 42 data points belonging to the Common Scab class. It classified 10 data points belonging to the Common Scab class as Black Scurf. It classified 3 data points belonging to the Common Scab class as Dry Rot. It classified 6 data points belonging to the Common Scab class as Miscellaneous. It classified 1 data point belonging to the Common Scab class as Pink Rot. In total, it incorrectly classified 20 data points belonging to the Common Scab class. It correctly classified 35 data points belonging to the Dry Rot class. It classified 9 data points belonging to the Dry Rot class as Blackleg. It classified 4 data points belonging to the Dry Rot class as Common Scab. It classified 1 data point belonging to the Dry Rot class as Healthy Potatoes. It classified 10 data points belonging to the Dry Rot class as Miscellaneous. It incorrectly classified 1 data point belonging to the Dry Rot class as Pink Rot. In total, it incorrectly classified 25 data points belonging to the Dry Rot class. It correctly classified 74 data points belonging to the Healthy Potatoes class. It classified 1 data point belonging to the Healthy Potatoes class as Black Scurf. It classified 2 data points belonging to the Healthy Potatoes class as Common Scab. It classified 1 data point belonging to the Healthy Potatoes class as Dry Rot. It classified 2 data points belonging to the Healthy Potatoes class as Miscellaneous. In total, it incorrectly classified 6 data points belonging to the Healthy Potatoes class. It correctly classified 40 data points belonging to the Miscellaneous class. It classified 4 data points belonging to the Miscellaneous class as Black Scurf. It classified 9 data points belonging to the Miscellaneous class as Blackleg. It classified 5 data points belonging to the Miscellaneous class as Common Scab. The data sample incorrectly classified 8 data points belonging to the Miscellaneous class as Dry Rot. It classified 4 data points belonging to the Miscellaneous class as Healthy Potatoes. It classified 4 data points belonging to the Miscellaneous class as Pink Rot. In total, it incorrectly classified 25 data points belonging to the Miscellaneous class. It correctly classified 43 data points belonging to the Pink Rot class. It classified 5 data points belonging to the Pink Rot class as Blackleg. It classified 1 data point belonging to the Pink Rot class as Common Scab. It classified 3 data points belonging to the Pink Rot class as Dry Rot. It classified 5 data points belonging to the Pink Rot class as Miscellaneous. In total, it incorrectly classified 14 data points belonging to the Pink Rot class. The graph of the performance metrics is given in Figure 8.

Model	Accuracy	F1 Score	Precision	Recall
ANN	0.685	0.685	0.686	0.685
KNN	0.548	0.536	0.548	0.548
SVM	0.656	0.660	0.660	0.656
LR	0.670	0.670	0.670	0.670

Figure 8. Performance Metrics Data

Examining Figure 8, the ANN model has the highest classification success, while the KNN model has the lowest. The classification success of the LR model is 0.670, and the classification success of the SVM model is 0.656. When other performance metrics are examined, it is seen that the F1 Score, Precision, and Recall metric values show parallelism with the classification success of the models. When the classification successes and F1 Score, Precision, and Recall metrics are examined, it can be said that all models show a success rate of 54.8% and above. One of the main reasons for the classification success rates falling below expectations is that the dataset consists of only 451 images, resulting in a relatively limited sample size for deep learning-based feature extraction. Furthermore, some disease classes in the dataset exhibited visually very similar symptoms, leading to confusion between classes. The fact that the images were obtained at different resolutions and under different conditions also increased within-class variation, negatively impacting model performance. In addition, the features obtained from SqueezeNet in this study were classified using classical machine learning algorithms, and the class discrimination power that could be provided by deeper, end-to-end trained networks was not fully achieved. The study's seven-class problem presented a more challenging classification scenario compared to commonly used binary classification problems in the literature, thus lowering success rates.

4. Conclusion

Image processing methods have become frequently used in identifying potato diseases recently. Accurate analysis of the data obtained from these methods allows for the rapid determination of potato production quality. Based on this, this study classified data obtained from 451 different potato photographs. The highest classification success rate was obtained from the ANN model at 68.5%. The lowest classification success rate was obtained from the KNN model at 54.8%.

Examining the results, it can be said that the machine learning models used in this study can be used in potato disease classification problems. Data from 451 different potato samples were used. In this case, the success of the models may decrease in some real-life tests. To overcome this problem, the number of data points can be increased. In addition to increasing the number of data points, higher results can be obtained in real-life tests using different classification methods.

With the classification models proposed in this study and the data obtained from sensors, potato quality can be quickly determined in production facilities, harvesting networks, packaging facilities, and businesses where potatoes are consumed. This will enable consumers to consume potatoes of the highest quality.

Declaration of Ethical Standards

This research does not involve direct interaction with human participants or animals. Accordingly, ethical approval and informed consent were not required.

Credit Authorship Contribution Statement

All authors contributed substantially and equally to this study. The processes of conceptualization, methodology development, software implementation, validation, formal analysis, investigation, data curation, manuscript drafting, review and editing, as well as visualization were carried out collaboratively. All authors have reviewed and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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Data Availability

The dataset used in this study was obtained from a publicly available source and subsequently processed by the authors for classification purposes. Further details regarding the processed dataset are available from the corresponding author upon reasonable request.

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