

# An Effective Approach for Potato Leaf Disease Classification Using Deep Learning

Sukru Aykat

**Abstract**—This study comparatively investigates the performance of deep learning and hybrid approaches for the detection and classification of potato leaf diseases (early blight, late blight, and healthy). In the first stage, direct image classification was performed using pre-trained deep learning models DenseNet201, ResNet50V2, VGG16, and Xception. Of these models, the VGG16 model achieved the highest accuracy. In the second stage, the same deep learning models were used as feature extractors, and the resulting features were classified using traditional machine learning algorithms, SVM, KNN, RF, and XGB. These hybrid approaches provided a significant increase in classification performance. The findings revealed that DenseNet201's combination of SVM and XGB exhibited superior performance with an overall accuracy rate of 99.31%. These results demonstrate that the powerful feature extraction capabilities of deep learning architectures, combined with the effective classification power of traditional machine learning algorithms, provide higher accuracy and reliability compared to the direct deep learning approach. The study highlights the potential of hybrid approaches, particularly for applications such as agricultural image processing and plant disease detection.

**Index Terms**— potato leaf disease, agriculture, deep learning, machine learning.

## I. INTRODUCTION

Potatoes, one of the world's most important food crops, play a significant role in both the agricultural economy and global food security [1]. Potatoes are a rich source of vitamins, minerals, and phytochemicals that contribute to improved digestion, immune function, and heart health [2]. Their high starch content provides significant energy, while resistant starch acts as a prebiotic, supporting intestinal health [3]. However, several obstacles exist in the production of this staple crop, the most significant of which is the increase in foliar diseases [1]. Potato foliar diseases pose a serious threat to the sustainability of potato production, yield, and quality. A wide variety of pathogens, including fungi, bacteria, viruses, and environmental stresses, cause potato foliar diseases [4]. Late blight and early blight are the most common foliar diseases of potatoes worldwide, causing significant yield losses in most potato-growing regions [5, 6]. Characteristic foliar symptoms of late blight appear as small, water-soaked spots on the tips or margins of lower leaves [7, 8]. The disease progresses along the leaflets and petioles, causing dark brown discoloration of the

leaf stalks and stems of potato crops [8, 9]. Early blight in potato appears as dark brown to black lesions with concentric rings on senescent leaves [10, 11].

Leaf diseases can cause significant economic losses and pose a threat to food security [12]. These problems are primarily due to the late diagnosis of potato diseases and errors in disease identification. Rapid and accurate identification of diseases in potato plants is crucial for reducing the impact of diseases on plants [13]. Traditional agricultural practices for plant disease detection often rely on manual visual inspection, which is expensive, time-consuming, and highly subjective and biased [14]. Farmers usually identify diseases in plants approximately and based on assumptions, which can lead to misidentification due to similarities in leaf symptoms that are difficult to determine at a glance. Furthermore, preventive measures taken by farmers can be ineffective and can damage crops due to insufficient information and misinterpretation of disease intensity, overdosage, or underdosage [15].

With the use of technology, diseases are detected at early stages, and crop productivity has been shown to increase [16]. Recent advances in machine learning and image processing technologies have enabled the development of automated techniques for detecting plant leaf diseases. These techniques effectively and accurately detect plant leaf diseases in a short time without human intervention. Deep learning has been widely applied in agriculture [17].

Recently, many deep learning architectures have been proposed for plant disease classification. The most prominent of these is the convolutional neural network (CNN). ECA is a supervised deep learning model inspired by the biological nervous system, boasting significant performance compared to other models. CNN consists of many neurons and multilayer convolutional layers to learn features [18, 19].

Many techniques and methods have been used to classify diseases from potato leaf images. Iqbal et al. [20] proposed an image processing and machine learning-based automated system for identifying and classifying potato leaf diseases. They achieved an accuracy of 97% using the Random Forest algorithm. Chakraborty et al. [21] presented a three-class classification to detect blights on potato leaves and classify them as normal, early blight, and late blight leaves. Training was performed on VGG-16, VGG-19, MobileNet, and ResNet-50 CNN models. After fine-tuning VGG 16, they achieved a test accuracy of 97.89%. Sholihati et al. [13] utilized VGG16 and VGG19 to classify potato leaf diseases, achieving an accuracy of 91% with VGG16. Jha et al. [22] proposed a deep learning ensemble model that combines ResNet, MobileNet, and Inception models to improve potato leaf disease prediction.

Sukru Aykat, Department of Computer Engineering Mardin Artuklu University, Mardin, Turkey, (e-mail: sukruaykat@artuklu.edu.tr).



<https://orcid.org/0000-0003-1738-3696>

Manuscript received Sep 02, 2025; accepted Oct 21, 2025.

DOI: 10.17694/bajece.1776532

They achieved an overall accuracy of 98.86% with this model, demonstrating its effectiveness in classifying potato leaf diseases. Ashikuzzaman et al. [23] conducted a comparative study using nine transfer learning deep CNN models to detect potato leaf diseases. DenseNet201 achieved the highest validation accuracy of 96% with low losses, demonstrating the effectiveness of transfer learning in disease detection. Rabbia Mahum et al. [24] used the pre-trained DenseNet201 model in their study. They achieved a test accuracy of 97.2%. Choyon Chandra Bonik et al. [25] utilized a CNN model to accurately identify and detect potato leaf diseases through image processing, achieving a model accuracy of 94.2%. Chen et al. [26] developed a deep learning-based technique for identifying potato diseases, achieving an accuracy of 97.33%. Sarah et al. [27] proposed a deep learning model based on adaptive transfer learning for classifying potato leaf disease. They achieved a test accuracy of 98%.

This study aims to detect potato leaf diseases using deep learning methods. For this purpose, four different deep learning models were used for disease detection. Additionally, these deep learning models were used as feature extractors to classify potato leaf disease images using support vector machine (SVM), K-Nearest Neighbor (KNN), random forest (RF), and XGBoost (XGB) classifiers. Performance evaluations were conducted using the metrics of the deep models used.

This article is presented briefly as follows: Section 2 provides information about the dataset and the deep learning models. This section also includes detailed information about the classifiers and the proposed method. The experimental findings obtained in the study are presented in Section 3. The final section consists of the conclusions.

## II. MATERIALS AND METHODS

In this study, we analyzed the results of CNN models and the proposed models on a potato leaf image dataset to detect potato leaf diseases. The CNN models used in this study are DenseNet201, ResNet50V2, Xception, and VGG16. We also proposed a model that uses SVM, KNN, RF, and XGB classifiers.

### A. CNN Models

DenseNet201 [28] is a CNN that uses dense blocks to establish dense connections between layers, with all levels directly connected. In a feedforward technique, each layer is connected to all other layers. When a layer is created, the feature maps of all previous layers are considered independent inputs for each layer. In contrast, the feature maps of the current layer are connected as inputs to all subsequent layers. Advantages of DenseNets include eliminating the vanishing gradient problem, enhancing feature propagation, facilitating feature reuse, and achieving a significant reduction in the number of parameters.

ResNet, proposed by He et al. [29] is an CNN-based model consisting of 48 convolutional layers. The other two layers are a maximum pooling layer and an average pooling layer. The ResNet architecture allowed CNN to work with multiple layers. Deep neural networks with multiple successive layers tend to produce higher training error percentages than models with fewer layers. This architecture utilized residual connections and

residual functions, thus reducing the training error of the successively added layers of deep neural networks.

Xception [30] is a variant of the Inception architecture that uses standard depth-based separable convolutions. The Xception architecture features 36 convolutional layers as its base for feature extraction. Excluding the first and last layers, the convolutional layers are divided into 14 modules, each surrounded by linear residual connections. This model uses depth-based separable convolutions instead of standard inception modules with a point-wise convolution ( $1 * 1$ ).

VGG16 [31] is a 16-layer network introduced in 2014 by Simonyan and Zisserman from the Visual Geometry Group Laboratory at the University of Oxford. VGG16 consists of 13 convolutional layers and three fully connected layers. The model achieved a test data accuracy of 92.77% on ImageNet, a dataset comprising 14 million images.

### B. Classifiers

SVM classifies both linear and nonlinear data [32]. SVM performs classification by transforming the original training data into a multidimensional space and constructing a higher-dimensional hyperplane [33].

The KNN algorithm is a supervised machine learning algorithm primarily used for classification [34]. The  $k$  value represents the number of neighboring data points to be examined for the data to be classified. In this study,  $k$  is set to one, and the Minkowski distance is used as the distance function.

RF is a collection of decision trees, where each tree is constructed from a bootstrapped version of the training dataset. Each tree is grown using the principle of recursive partitioning, where the same node partitioning procedure is repeatedly applied, starting from the root node, until specific stopping rules are met. Predictive power comes from combining many weak learners (decision trees). It performs well if the correlations between trees in the forest are low [35].

XGB is one of the applications of gradient boosting machines, known as one of the best-performing algorithms used for supervised learning. It is used for both regression and classification problems. XGB is preferred by data scientists due to its high execution speed outside of core computation [36].

### C. Dataset

The Plant Village dataset consists of nine plant leaf images [37]. In our study, we used the potato leaf images included in this dataset. The resulting dataset comprises 7,128 potato leaf images, categorized into three classes: Late\_Blight, Early\_Blight, and Healthy. The resolution of the JPG images in the dataset is 256 x 256 pixels. The distribution of the training, validation, and test images in the dataset is shown in Table 1.

TABLE I. DISTRIBUTION OF THE DATASET

Classes	Training	Validation	Testing
Early_Blight	1,939	436	49
Healthy	1,824	410	46
Late_Blight	1,939	436	49
Total	5,702	1,282	144

D. Proposed Method

In this study, a hybrid approach combining deep learning and machine learning is proposed to automatically detect early blight, late blight, and healthy leaf classes in potato leaves. The proposed method consists of two stages. In the first stage, direct classification is performed using different deep learning architectures; in the second stage, deep features obtained from the deep learning models are transferred to traditional machine learning algorithms.

In the first stage, pre-trained CNN architectures DenseNet201, ResNet50V2, Xception, and VGG16 were used. These models were retrained using a transfer learning approach and optimized to classify potato leaf images into three different classes. This directly leverages the high accuracy potential and learning capacity of the CNN models.

In the second stage, these CNN models were used as feature extractors. For this purpose, the last classification layer of each model was removed, resulting in the deep features obtained from the intermediate layers as vectors. These features were fed as input data to the SVM, KNN, RF, and XGB algorithms, and each machine learning model performed classification separately. This approach enables a comparative study of how effectively deep learning-based features facilitate classification compared to different statistical and tree-based machine learning methods. The general design of the proposed method is shown in Figure 1.

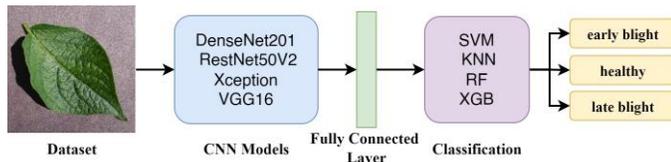


Fig. 1. Model design of the proposed method

The parameter values of the CNN models used in this study are shown in Table 2.

TABLE II. PARAMETER VALUES OF CNN MODELS

Parameters	Values
Image Size	128 x 128
Learning Rate	0.0001
Batch Size	16
Training Number	50
Optimization	Adam

In our study, a confusion matrix was used to evaluate the performance of the models considered. Accuracy, Recall, Precision, and F1-score metrics were used as performance metrics. False Negative (FN), False Positive (FP), True Negative (TN), and True Positive (TP) indices were used to calculate the performance metrics [38].

$$Accuracy = (TP+TN) / (TP+TN+FP +FN) \tag{1}$$

$$Recall = TP / (TP+FN) \tag{2}$$

$$Precesion = TP / (TP+FP) \tag{3}$$

$$F1=2*(Recall*Precesion)/(Recall+Precesion) \tag{4}$$

III. RESULTS AND DISCUSSION

A. Performance Results of CNN Models

In this analysis, the success rates of CNN models were compared on the potato leaves dataset. Four CNN models were trained on the potato leaves dataset. The softmax function was used to classify the four models. The complexity matrices of the CNN models are shown in Figure 2. Upon examining the results, it is noteworthy that all models generally achieved high classification success; however, the types of errors varied between classes.

The DenseNet201 model was found to be quite successful in classifying the Healthy class. It correctly classified 44 of 46 healthy leaves, mislabeling only one as Early\_Blight and one as Late\_Blight. For the Early\_Blight class, it correctly predicted 28 of 49 samples, misclassifying 20 as Healthy and one as Late\_Blight. This suggests that early blight symptoms can be similar to healthy leaves, and the model is having difficulty distinguishing between these two classes.

The ResNet50V2 model achieved similar accuracy to DenseNet201 in the Early\_Blight class, with 29 correct predictions. However, it achieved higher accuracy in the Healthy class, with 45 correct predictions. However, for the Late\_Blight class, it achieved 43 correct classifications, and class confusion remained generally low.

The VGG16 model achieved very high accuracy in the Healthy and Late\_Blight classes, with 46 and 49 correct predictions, respectively. However, while 25 correct predictions were made in the Early\_Blight class, 12 images were misclassified as Healthy, and 12 images were misclassified as Late\_Blight. This suggests that the model has relatively more difficulty distinguishing Early\_Blight from the other classes.

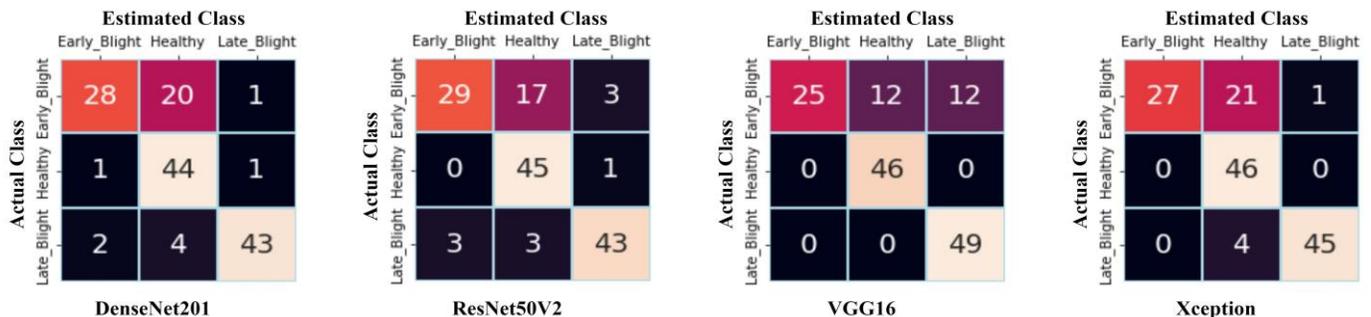


Fig. 2. Complexity matrices of CNN models

The Xception model demonstrated high accuracy with 46 correct predictions in the Healthy class and 45 correct classifications in the Late\_Blight class. Despite 27 correct predictions in the Early\_Blight class, 21 samples were misclassified as Healthy. This type of error was also observed in the DenseNet201 model, indicating that the two models experienced similar classification difficulty.

Overall, all CNN models achieved high accuracies in the Healthy and Late\_Blight classes, but lower accuracy was achieved in the Early\_Blight class compared to the other classes. This suggests that the Early\_Blight leaf images are visually similar to the other classes, and that the CNN models have difficulty distinguishing features.

The performances of the four CNN models trained on the dataset are shown in Table 3. The results reveal significant differences in overall accuracy among the models. The VGG16 model achieved the highest overall accuracy of 83.33%, followed by Xception (81.94%), ResNet50V2 (81.25%), and DenseNet201 (79.86%). This finding suggests that the VGG16 architecture learns and classifies visual features of potato leaf diseases more effectively than the other architectures.

TABLE III. COMPLEXITY MATRIX RESULTS OF CNN MODELS

Models	Classes	Precision (%)	Recall (%)	F1-Score	General Accuracy
DenseNet201	Early_Blight	90.32	57.14	0.70	79.86%
	Healthy	64.70	95.65	0.77	
	Late_Blight	95.56	87.76	0.91	
ResNet50V2	Early_Blight	90.63	59.18	0.72	81.25%
	Healthy	69.23	97.83	0.81	
	Late_Blight	91.49	87.76	0.90	
VGG16	Early_Blight	100	51.02	0.68	83.33%
	Healthy	79.31	100	0.88	
	Late_Blight	80.33	100	0.89	
Xception	Early_Blight	100	55.10	0.71	81.94%
	Healthy	64.79	100	0.79	
	Late_Blight	97.83	91.84	0.95	

However, a more detailed picture emerges when the model performances are examined by class. For the Early\_Blight class, the VGG16 and Xception models achieved Precision values of 100%, indicating that no sample they predicted belonged to this class belonged to any other class. However, the low Recall values of these two models, at 51.02% and 55.10% respectively, indicate that these models incorrectly assigned a significant portion of images containing early blight symptoms to other classes. This suggests that VGG16 and Xception have difficulty distinguishing early-stage disease symptoms or are confusing these symptoms with features of other classes (especially healthy leaves).

For the Healthy and Late\_Blight classes, the models performed better. In particular, the VGG16 model achieved

Recall values of 100% in both classes, indicating that it correctly identified all samples belonging to these classes. Similarly, the Xception model achieved a Precision value of 100% in the Healthy class. These high-precision values indicate that there are visually significant differences, particularly between late-stage disease and healthy leaves, and that deep learning models effectively capture these differences. Overall, the results indicate that different CNN architectures exhibit varying degrees of sensitivity to visual features in early and late-stage disease, and this can be more clearly understood by examining class-based performance metrics rather than overall accuracy. Furthermore, the fact that the VGG16 model achieved the highest overall accuracy suggests that this architecture is more suited to the characteristics of the dataset.

*B. Performance Results of Hybrid Models*

In the second phase of our study, we examined the performance of hybrid approaches in which CNN models were used as feature extractors and the resulting feature vectors were classified using traditional machine learning algorithms.

We investigated the impact of the high-level feature vectors obtained from the DenseNet201 model on the classification performance of traditional machine learning algorithms. The confusion matrices shown in Figure 3 demonstrate the classification capabilities of the combination of DenseNet201 model-based feature extraction and machine learning algorithms. Among these hybrid approaches, the SVM and XGB models exhibited the most remarkable performance. The XGB model correctly classified 49 instances of the Early\_Blight class, 46 instances of the Healthy class, and 48 instances of the Late\_Blight class. It incorrectly labeled only one instance of the Late\_Blight class as Healthy. Similarly, the SVM model correctly predicted 48 instances of the Early\_Blight class, but misclassified only one instance as Late\_Blight. SVM correctly predicted both the Healthy and Late\_Blight classes. These results demonstrate that the high-level features extracted by DenseNet201 are highly discriminatory for these two powerful machine learning algorithms.

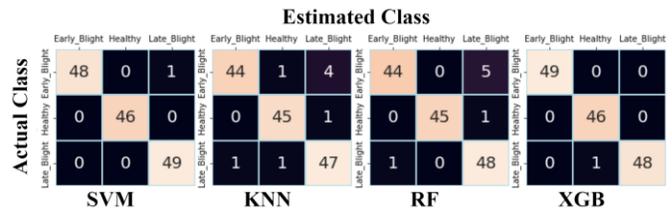


Fig. 3. Complexity matrices of DenseNet201 and classifiers

While the KNN and RF models also demonstrated high performance, they misclassified more frequently than the SVM and XGB models. The KNN model mislabeled four Early\_Blight samples as Late\_Blight, while the RF model misclassified five samples from the same class. This suggests that algorithms such as KNN and RF have some difficulty distinguishing the subtle differences between the complex visual features of early blight and late blight diseases. The results presented in Table 4 clearly demonstrate that this hybrid approach achieves exceptional success in classifying potato leaf diseases. In particular, the SVM and XGB hybrid models

showed superior performance compared to the other models. Both models achieved an overall accuracy rate of 99.31%, making them the most successful classifiers on the dataset.

TABLE IV. ANALYSIS RESULTS OF DENSENET201 AND CLASSIFIERS

Models	Classes	Precision (%)	Recall (%)	F1-Score	General Accuracy
SVM	Early_Blight	100	97.96	0.99	<b>99.31%</b>
	Healthy	100	100	1.00	
	Late_Blight	98	100	0.99	
KNN	Early_Blight	97.78	89.80	0.94	94.44%
	Healthy	95.74	97.83	0.97	
	Late_Blight	90.38	95.92	0.93	
RF	Early_Blight	97.78	89.80	0.94	95.14%
	Healthy	100	97.83	0.99	
	Late_Blight	88.89	97.96	0.93	
XGB	Early_Blight	100	100	1.00	<b>99.31%</b>
	Healthy	97.87	100	0.99	
	Late_Blight	100	97.96	0.99	

When examined by class, the DenseNet201+SVM model achieved 100% Precision values in the Early\_Blight and Healthy classes, and 100% Recall values in the Healthy class. This demonstrates that the model completely correctly identified healthy leaves, and that all samples it labeled as Early\_Blight actually belonged to this class. Similarly, the DenseNet201+XGB model achieved 100% Precision values in the Early\_Blight and Late\_Blight classes, and 100% Recall values in the Healthy and Late\_Blight classes. These high metrics demonstrate that deep learning-based features are highly discriminatory against powerful machine learning algorithms such as SVM and XGB.

The KNN and RF models also achieved high overall accuracy rates of 94.44% and 95.14%, respectively. While the performance of these models is not as excellent as that of SVM and XGB, the F1-score metrics, which are mostly above 0.90, indicate that they perform the classification task quite successfully. However, the lower Precision and Recall values of these models compared to SVM and XGB suggest that some features extracted by DenseNet201 bias the neighbor detection mechanisms of KNN or the tree-based decision mechanisms of RF towards minor misclassifications.

The performance of hybrid classification models created using the ResNet50V2 model as a feature extractor was examined. The confusion matrices shown in Figure 4 clearly demonstrate the success of these hybrid approaches in classifying potato leaf diseases. The findings suggest that the features extracted by ResNet50V2 are suitable for creating high-accuracy classification models when combined with various machine learning algorithms.

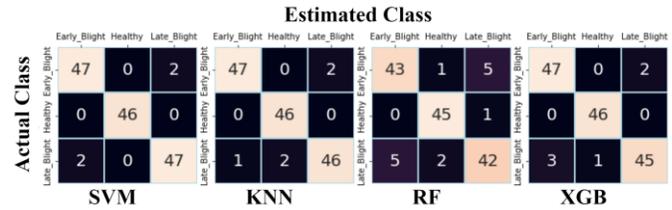


Fig. 4. Complexity matrices of ResNet50V2 and classifiers

The results show that the SVM and XGB hybrid models outperformed the others. Both models correctly classified 47 examples in the Early\_Blight class and 46 examples in the Healthy class. It is noteworthy that only in the Late\_Blight class, SVM mislabeled two examples as Early\_Blight, while XGB mislabeled three examples as Early\_Blight and one example as Healthy. Despite this, both models achieved high correct prediction rates and demonstrated strong classification performance.

While the KNN and RF models also demonstrated high performance, they misclassified more than the SVM and XGB. Specifically, the RF model performed the worst in this class, mislabeling five examples in the Early\_Blight class as Late\_Blight and one example as Healthy. Similarly, the KNN model misclassified one example in the Late\_Blight class as Early\_Blight and two examples as Healthy. This indicates that features obtained from ResNet50V2 exhibit some overlap between some neighboring samples, particularly between the Early\_Blight and Late\_Blight classes, which can slightly degrade the performance of algorithms such as KNN and RF.

Table 5 presents the performance metrics of hybrid classification models constructed using feature vectors derived from ResNet50V2. The results demonstrate that ResNet50V2 functions as a powerful feature extractor, and these features, when combined with different machine learning algorithms, produce highly accurate classification models.

TABLE V. ANALYSIS RESULTS OF RESNET50V2 AND CLASSIFIERS

Models	Classes	Precision (%)	Recall (%)	F1-Score	General Accuracy
SVM	Early_Blight	95.92	95.92	0.96	<b>97.22%</b>
	Healthy	100	100	1.00	
	Late_Blight	95.92	95.92	0.96	
KNN	Early_Blight	97.92	95.92	0.97	96.52%
	Healthy	95.83	100	0.98	
	Late_Blight	95.83	93.88	0.95	
RF	Early_Blight	89.59	87.76	0.89	90.28%
	Healthy	93.75	97.83	0.94	
	Late_Blight	87.50	85.71	0.87	
XGB	Early_Blight	94	95.92	0.95	95.83%
	Healthy	97.87	100	0.99	
	Late_Blight	95.74	91.84	0.94	

Among the analyzed models, the SVM hybrid model exhibited the highest performance with an overall accuracy rate of 97.22%. Specifically, for the Healthy class, the SVM model achieved 100% accuracy in both Precision and Recall. This finding demonstrates that ResNet50V2 is extremely capable of distinguishing the characteristic features of healthy leaves, and that the SVM generates a perfect separating hyperplane based on these features. In the Early\_Blight and Late\_Blight classes, the Precision and Recall values are as high as 95.92%, proving that this model also detects diseases effectively.

Other hybrid models also demonstrated similarly high performance. The KNN model followed closely behind the SVM, with an overall accuracy of 96.52%, while the XGB model achieved an accuracy of 95.83%. Both models demonstrated 100% recall in the Healthy class, successfully recognizing healthy growth. However, the RF model's lower Precision and Recall values, particularly in the Early\_Blight and Late\_Blight classes (89.59% and 87.50%, respectively), suggest that this model is less accurate than the others. Overall, all hybrid models outperformed the ResNet50V2 model alone.

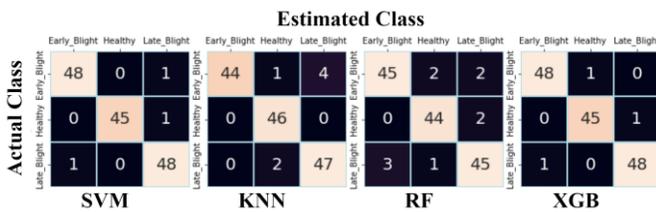


Fig. 5. Complexity matrices of VGG16 and classifiers

Performance metrics of the VGG16 hybrid models as a feature extractor. The mixed matrices presented in Figure 5 demonstrate that these approaches are highly successful in classifying potato leaf diseases. These findings confirm the effective performance of combining traditional machine learning with updates on high-level image features labeled from VGG16.

Examination of the matrices shows that the SVM and XGB hybrid models outperformed the others. The SVM model correctly classified 48 samples in the Early\_Blight class, 45 samples in the Healthy class, and 48 samples in the Late\_Blight class. It mislabeled only one Early\_Blight sample as Late\_Blight and one Healthy sample as Late\_Blight. Similarly, the XGB model correctly predicted 48 samples in the Early\_Blight class, 45 samples in the Healthy class, and 48 samples in the Late\_Blight class. The high number of correct predictions achieved by both models on the main diagonal demonstrates that the features obtained from VGG16 are sufficiently discriminatory for powerful algorithms like SVM and XGB.

The KNN and RF models also demonstrated high performance, but they misclassified more frequently than the SVM and XGB. Specifically, the KNN model correctly predicted 44 samples in the Early\_Blight class, while misclassifying one as Healthy and four as Late\_Blight. Similarly, the RF model mislabeled two instances from the Early\_Blight class as Healthy and two instances from the Late\_Blight class as Late\_Blight. This suggests that the features obtained from VGG16 exhibit some overlap between

neighboring instances, particularly between Early\_Blight and other classes, which can slightly degrade the performance of algorithms such as KNN and RF. However, overall, all hybrid models achieved higher performance compared to VGG16 alone.

TABLE VI. ANALYSIS RESULTS OF VGG16 AND CLASSIFIERS

Models	Classes	Precision (%)	Recall (%)	F1-Score	General Accuracy
SVM	Early_Blight	97.96	97.96	0.98	<b>97.92%</b>
	Healthy	100	97.83	0.99	
	Late_Blight	96	97.96	0.7	
KNN	Early_Blight	100	89.80	0.95	95.14%
	Healthy	93.88	100	0.97	
	Late_Blight	92.16	95.92	0.94	
RF	Early_Blight	93.75	91.84	0.93	93.06%
	Healthy	93.62	95.65	0.95	
	Late_Blight	91.84	91.84	0.92	
XGB	Early_Blight	97.96	97.96	0.98	<b>97.92%</b>
	Healthy	97.83	97.83	0.98	
	Late_Blight	97.96	97.96	0.98	

Table 6 presents the performance metrics of hybrid classification models constructed using feature vectors derived from the VGG16 model. The results demonstrate that VGG16 functions as a powerful feature extractor, and when combined with various machine learning algorithms, these features produce highly accurate classification models. In particular, the SVM and XGB hybrid models exhibited the highest performance with an overall accuracy rate of 97.92%. When examined by class, the SVM model achieved a precision of 100% and a recall of 97.83% for the Healthy class. This demonstrates that the model accurately identifies healthy leaves almost perfectly. It also performed well in the Early\_Blight class, with a precision and recall of 97.96%. Similarly, the XGB model achieved a precision and recall of 97.96% for the Early\_Blight and Late\_Blight classes. These high metrics demonstrate that the features extracted from VGG16 are highly discriminatory for powerful machine learning algorithms such as SVM and XGB.

The KNN and RF models also achieved high overall accuracies of 95.14% and 93.06%, respectively. While these models are not as accurate as SVM and XGB, their F1-score metrics, mostly above 0.90, demonstrate that they also perform the classification task quite successfully. The KNN's 100% Recall value for the Healthy class is particularly noteworthy. However, the RF model's lower Precision and Recall values for the Early\_Blight and Late\_Blight classes suggest that this model misclassifies more frequently than the others. Overall, all hybrid models were observed to outperform the VGG16 model alone.

The performance metrics of hybrid classification models, utilizing the Xception model as a feature extractor, were

examined. The confusion matrices presented in Figure 6 demonstrate that these approaches are highly successful in classifying potato leaf diseases. These findings confirm that deep visual features extracted from Xception generate high-accuracy classification models when combined with traditional machine learning algorithms.

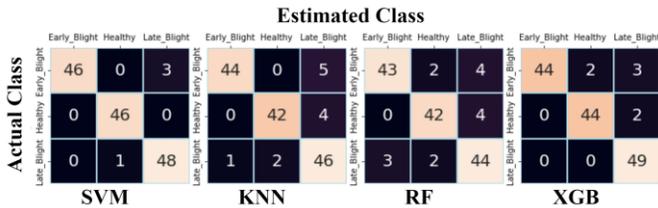


Fig. 6. Complexity matrices of Exception and classifiers

Examination of the matrices shows that the SVM and XGB hybrid models outperformed the others. The SVM model correctly classified all 46 samples in the Healthy class and achieved high success with 48 correct predictions in the Late\_Blight class. Despite making 46 correct predictions in the Early\_Blight class, it mislabeled three samples as Late\_Blight. The XGB model, on the other hand, performed similarly to SVM, correctly classifying 44 samples in the Healthy class and 49 samples in the Late\_Blight class. The high accuracy rates of these two models demonstrate that the features extracted by Xception are sufficiently discriminatory for powerful algorithms like SVM and XGB.

While the KNN and RF models also demonstrated high performance, they misclassified more samples than the SVM and XGB. Specifically, the KNN model mislabeled 5 samples from the Early\_Blight class, 4 samples from the Healthy class, and three samples from the Late\_Blight class, indicating some confusion between these classes. Similarly, the RF model also misclassified the Early\_Blight and Late\_Blight classes. This suggests that the features obtained from Xception exhibit some overlap between neighboring samples, particularly between Early\_Blight and other classes, which may slightly degrade the performance of algorithms such as KNN and RF. However, overall, all hybrid models achieved higher performance compared to Xception alone.

Table 7 presents the performance metrics of hybrid classification models constructed using feature vectors derived from the Xception model. The results demonstrate that Xception functions as a powerful feature extractor, and when combined with various machine learning algorithms, these features produce highly accurate classification models. In particular, the SVM hybrid model demonstrated the highest performance with an overall accuracy rate of 97.22%.

When examined by class, the SVM model achieved a Precision value of 100% for the Early\_Blight class and a Recall value of 100% for the Healthy class. This finding demonstrates that the SVM completely correctly identified healthy leaves, and that all instances labeled as Early\_Blight actually belonged to this class. Another successful model, XGB, stands out with its overall accuracy of 94.44%. XGB achieved a Precision value of 100% for the Early\_Blight class and a Recall value of 100% for the Late\_Blight class. These high metrics demonstrate that the features extracted from Xception are highly discriminatory against powerful algorithms, such as SVM and XGB.

The KNN and RF models also achieved high overall accuracies of 91.67% and 89.59%, respectively. While the performance of these models is not as excellent as that of SVM and XGB, their F1-score metrics, ranging from 0.87 to 0.94, indicate that they also perform the classification task quite successfully. However, the lower Precision and Recall values of these models compared to SVM and XGB, particularly in the Late\_Blight class, suggest that some features extracted from Xception bias the neighbor detection mechanisms of KNN or the tree-based decision mechanisms of RF towards minor misclassifications. Overall, all hybrid models were observed to perform better than the Xception model alone.

TABLE VII. ANALYSIS RESULTS OF EXCEPTION AND CLASSIFIERS

Models	Classes	Precision (%)	Recall (%)	F1-Score	General Accuracy
SVM	Early_Blight	100	93.88	0.97	97.22%
	Healthy	97.87	100	0.99	
	Late_Blight	94.12	97.96	0.96	
KNN	Early_Blight	97.78	89.80	0.94	91.67%
	Healthy	95.46	91.30	0.93	
	Late_Blight	83.64	93.88	0.88	
RF	Early_Blight	93.48	87.75	0.91	89.59%
	Healthy	91.30	91.30	0.91	
	Late_Blight	84.62	89.80	0.87	
XGB	Early_Blight	100	89.80	0.95	94.44%
	Healthy	95.65	95.65	0.96	
	Late_Blight	90.74	100	0.95	

The overall accuracies of hybrid models using CNN architectures (DenseNet201, ResNet50V2, VGG16, Xception) as feature extractors, combined with machine learning algorithms (SVM, KNN, RF, XGB), were comparatively analyzed. The graph presented in Figure 7 clearly demonstrates that all hybrid models exhibited relatively high performance, but the accuracy rates varied depending on the model combination. These findings demonstrate the effectiveness of a hybrid methodology in classifying potato leaf diseases.

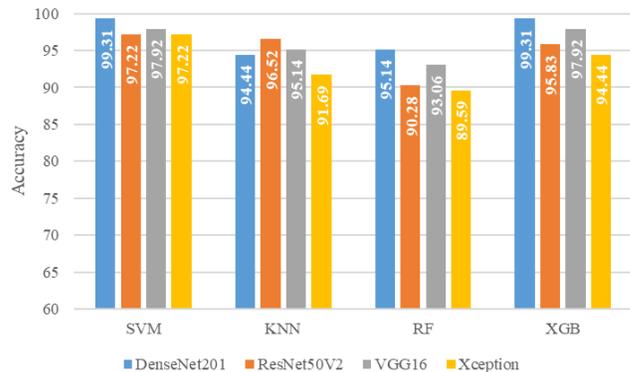


Fig. 7. Performance rates of hybrid models

The highest overall accuracies were achieved using the SVM and XGB classifiers. Among the hybrid models used with SVM, the most successful was DenseNet201+SVM, which achieved the highest accuracy rate of 99.31%. This was followed by VGG16+SVM (97.92%) and ResNet50V2+SVM (97.22%). Similarly, the XGB classifier also demonstrated high performance, with the highest accuracy rate of 99.31% recorded with the DenseNet201+XGB combination. These results demonstrate that DenseNet201 can extract the most discriminative features, and that powerful algorithms, such as SVM and XGB, can generalize best on these features.

On the other hand, the KNN and RF classifiers achieved lower, but still relatively high, accuracies compared to SVM and XGB. Among these models, the best performance was achieved by the combinations of ResNet50V2+KNN (96.52%) and VGG16+RF (95.14%), respectively. These findings demonstrate that the features extracted by VGG16 and ResNet50V2 can be effectively used even for algorithms such as KNN and RF.

Overall, all hybrid models achieved significantly higher performance compared to direct deep learning models. This comparison demonstrates that combining the high-level feature extraction power of deep learning models with the robust classification capabilities of traditional machine learning algorithms is the most suitable methodological approach for classifying potato leaf diseases.

#### Comparative Performance Analysis of Our Study with Other Studies in the Literature

TABLE VIII. COMPARATIVE PERFORMANCE ANALYSIS OF OUR STUDY WITH OTHER STUDIES IN THE LITERATURE

Research	Models	Dataset	Accuracy (%)
Iqbal et al. [20]	RF	PlantVillage	97.00
Chakraborty et al. [21]	VGG16 (fine tuned)	PlantVillage	97.89
Sholihati et al. [13]	VGG16	PlantVillage	91.00
Jha et al. [22]	ResNet, MobileNet, Inception, Stack Ensemble	PlantVillage	98.86
Ashikuzzaman et al. [23]	DenseNet201	PlantVillage	96.00
Rabbia Mahum et al. [24]	Efficient DenseNet	PlantVillage	97.20
Choyon Chandra Bonik et al. [25]	CNN Model Özel DataSet	Custom Dataset	94.20
Chen et al. [26]	MobS_Net	2018 AI Challenger Contest	97.33
Sarah et al. [27]	Customized VGG16 model	PlantVillage	98.00
<b>Our Study</b>	<b>DenseNet201 + DVM/XGB</b>	PlantVillage	<b>99.31</b>

As seen in Table 8, the findings of this study are consistent with the existing literature on the classification of potato leaf diseases and offer significant contributions, particularly by highlighting the superior performance of hybrid approaches. Studies such as Iqbal et al. [20] have shown that traditional machine learning algorithms can achieve accuracies as high as

97%, even with manually selected features. However, this approach increases the cost of feature engineering as the data grows larger and more complex. The hybrid approach employed in our study addresses this problem by leveraging the automatic feature extraction capabilities of deep learning models, achieving higher accuracy rates.

Most studies in the literature have focused on the direct classification performance of a single deep learning model, particularly through the use of transfer learning. Chakraborty et al. [21] achieved 97.89% accuracy with VGG16; Rabbia Mahum et al. [24] and Ashikuzzaman et al. [23] achieved accuracies close to 97% with DenseNet201. These results demonstrate the considerable power of single deep learning models. However, the highest accuracy we achieved in our direct deep learning analysis (83.33% for VGG16) suggests that these models may have limitations in generalizing to visual features specific to our dataset. This finding highlights the importance of model-data compatibility when utilizing direct deep learning models.

The most notable finding of our study is that the hybrid approach, which combines deep learning and machine learning, outperforms both direct deep learning models and many studies in the literature. In particular, processing the features obtained from DenseNet201 with robust classifiers such as SVM and XGB allowed us to achieve a record overall accuracy rate of 99.31%. Even the ensemble learning model proposed by Jha et al. [22], which achieved an accuracy of 98.86%, failed to match the performance of our most successful hybrid approach. This strongly supports the superiority of deep learning architectures in extracting distinctive feature vectors that represent the semantic content of images and the effectiveness with which these features can be utilized with traditional machine learning algorithms.

In conclusion, this study proposes that the most suitable methodological framework for the automatic detection of potato leaf diseases is a hybrid model that combines deep learning-based feature extraction with traditional machine learning classification. This approach leverages the synergy between complex hierarchical feature extraction and fast, efficient classification, offering both high accuracy and potentially better generalization. Future studies could expand the general applicability of this methodology by testing the performance of this hybrid approach across different crops and diseases.

#### IV. CONCLUSION

This study examined the comparative performance of deep learning and hybrid approaches for image-based detection of potato leaf diseases (early blight, late blight, healthy). The findings indicate that both methodologies are effective for this type of classification task, but the hybrid approach provides significantly higher accuracy and reliability.

In the initial analysis, direct image classification was performed using pre-trained deep learning models, including DenseNet201, ResNet50V2, VGG16, and Xception. Among these models, the VGG16 model exhibited the highest performance. However, when confusion matrices and class-based performance metrics (Precision and Recall) were

examined, it was observed that these models had difficulty distinguishing visually more subtle classes, such as early blight. This suggests that direct deep learning models may be limited in capturing subtle symptoms in the early stages of diseases. In the second analysis, a hybrid approach was adopted, using deep learning models as automatic feature extractors followed by classification using SVM, KNN, RF, and XGB machine learning algorithms. This methodology yielded a significant increase in classification performance compared to the first approach. Among the hybrid models, the DenseNet201 SVM and XGB combinations demonstrated superior performance, with an overall accuracy rate of 99.31%. This result indicates that combining the complex hierarchical feature extraction power of deep learning models with the efficient classification capabilities of powerful machine learning algorithms, such as SVM and XGB, can achieve nearly flawless performance. Other hybrid models achieved similarly high accuracies.

In conclusion, this study demonstrates that the most effective methodology for detecting potato leaf diseases is a hybrid approach in which high-level features derived from deep learning architectures are classified using traditional machine learning algorithms, rather than directly using deep learning models. This finding suggests that, particularly in applications such as agricultural image processing and disease detection, automating the feature engineering phase and processing these features with simpler yet more powerful classifiers can yield higher accuracy and generalization. Future work could focus on testing this hybrid approach on different plant diseases and datasets to examine its generalizability.

#### REFERENCES

- [1] A. Dogra, S. Kadry, B. Goyal, and S. Agrawal, "An efficient image integration algorithm for night mode vision applications," *Multimedia Tools and Applications*, vol. 79, no. 15–16, pp. 10995–11012, 2020. <https://doi.org/10.1007/S11042-018-6631-Z/TABLES/3>
- [2] J. Tian, J. Chen, X. Ye, and S. Chen, "Health benefits of the potato affected by domestic cooking: A review," *Food Chemistry*, vol. 202, pp. 165–175, 2016. <https://doi.org/10.1016/J.FOODCHEM.2016.01.120>
- [3] C.M. Andre, S. Legay, C. Iammarino, et al., "The Potato in the Human Diet: a Complex Matrix with Potential Health Benefits," *Potato Research*, vol. 57, no. 3, pp. 201–214, 2014. <https://doi.org/10.1007/s11540-015-9287-3>
- [4] A. Singh and H. Kaur, "Potato Plant Leaves Disease Detection and Classification using Machine Learning Methodologies," *IOP Conference Series: Materials Science and Engineering*, vol. 1022, no. 1, p. 012121, 2021. <https://doi.org/10.1088/1757-899X/1022/1/012121>
- [5] E. Aksoy, U. Demirel, A. Bakhsh, et al., "Recent Advances in Potato (*Solanum tuberosum* L.) Breeding," *Advances in Plant Breeding Strategies: Vegetable Crops: Volume 8: Bulbs, Roots and Tubers*, pp. 409–487, 2021. [https://doi.org/10.1007/978-3-030-66965-2\\_10](https://doi.org/10.1007/978-3-030-66965-2_10)
- [6] H.N. Fones, D.P. Bebbler, T.M. Chaloner, W.T. Kay, G. Steinberg, and S.J. Gurr, "Threats to global food security from emerging fungal and oomycete crop pathogens," *Nature Food*, vol. 1, no. 6, pp. 332–342, 2020. <https://doi.org/10.1038/S43016-020-0075-0>
- [7] V. Lehsten, L. Wiik, A. Hannukkala, et al., "Earlier occurrence and increased explanatory power of climate for the first incidence of potato late blight caused by *Phytophthora infestans* in Fennoscandia," *PLOS ONE*, vol. 12, no. 5, p. e0177580, 2017. <https://doi.org/10.1371/JOURNAL.PONE.0177580>
- [8] S.S. Ray, N. Jain, R.K. Arora, S. Chavan, and S. Panigrahy, "Utility of Hyperspectral Data for Potato Late Blight Disease Detection," *Journal of the Indian Society of Remote Sensing*, vol. 39, no. 2, pp. 161–169, 2011. <https://doi.org/10.1007/S12524-011-0094-2/TABLES/6>
- [9] P. Nolte, J. Miller, K.M. Duellman, A.J. Gevens, and E. Banks, "Disease Management," *Potato Production Systems*, pp. 203–257, 2020. [https://doi.org/10.1007/978-3-030-39157-7\\_9](https://doi.org/10.1007/978-3-030-39157-7_9)
- [10] A. Shukla and V. Ratan, "Management of Early Blight of Potato by Using Different Bioagents as Tuber Dressing and its Effect on Germination and Growth," *International Journal of Current Microbiology and Applied Sciences*, vol. 8, no. 06, pp. 1965–1970, 2019. <https://doi.org/10.20546/IJCMAS.2019.806.233>
- [11] I.K. Abuley and B.J. Nielsen, "Evaluation of models to control potato early blight (*Alternaria solani*) in Denmark," *Crop Protection*, vol. 102, pp. 118–128, 2017. <https://doi.org/10.1016/J.CROPRO.2017.08.012>
- [12] A. Abbas, U. Maqsood, S. Ur Rehman, K. Mahmood, T. Alsaedi, and M. Kundi, "An Artificial Intelligence Framework for Disease Detection in Potato Plants," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 12628–12635, 2024. <https://doi.org/10.48084/ETASR.6456>
- [13] R.A. Sholihati, I.A. Sulistijono, A. Risnumawan, and E. Kusumawati, "Potato Leaf Disease Classification Using Deep Learning Approach," *IES 2020 - International Electronics Symposium: The Role of Autonomous and Intelligent Systems for Human Life and Comfort*, pp. 392–397, 2020. <https://doi.org/10.1109/IES50839.2020.9231784>
- [14] S. Iftikhar, A.A. Shahid, S.A. Halim, et al., "Discovering novel *Alternaria solani* succinate dehydrogenase inhibitors by in silico modeling and virtual screening strategies to combat early blight," *Frontiers in Chemistry*, vol. 5, no. NOV, p. 300609, 2017. <https://doi.org/10.3389/FCHEM.2017.00100/BIBTEX>
- [15] P. Tm, A. Pranathi, K. Saiashritha, N.B. Chittaragi, and S.G. Koolagudi, "Tomato Leaf Disease Detection Using Convolutional Neural Networks," *2018 11th International Conference on Contemporary Computing, IC3 2018*, p. 2018. <https://doi.org/10.1109/IC3.2018.8530532>
- [16] M. Yang, P. Kumar, J. Bhola, and M. Shabaz, "Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit," *International Journal of System Assurance Engineering and Management*, vol. 13, no. 1, pp. 322–330, 2022. <https://doi.org/10.1007/S13198-021-01415-1/TABLES/1>
- [17] K.P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018. <https://doi.org/10.1016/J.COMPAG.2018.01.009>
- [18] K. Golhani, S.K. Balasundram, G. Vadamalai, and B. Pradhan, "A review of neural networks in plant disease detection using hyperspectral data," *Information Processing in Agriculture*, vol. 5, no. 3, pp. 354–371, 2018. <https://doi.org/10.1016/J.INPA.2018.05.002>
- [19] M. Aamir, M. Irfan, T. Ali, et al., "An Adoptive Threshold-Based Multi-Level Deep Convolutional Neural Network for Glaucoma Eye Disease Detection and Classification," *Diagnostics 2020, Vol. 10, Page 602*, vol. 10, no. 8, p. 602, 2020. <https://doi.org/10.3390/DIAGNOSTICS10080602>
- [20] M.A. Iqbal and K.H. Talukder, "Detection of Potato Disease Using Image Segmentation and Machine Learning," *2020 International Conference on Wireless Communications, Signal Processing and Networking, WiSPNET 2020*, pp. 43–47, 2020. <https://doi.org/10.1109/WISPNET48689.2020.9198563>
- [21] K.K. Chakraborty, R. Mukherjee, C. Chakraborty, and K. Bora, "Automated recognition of optical image based potato leaf blight diseases using deep learning," *Physiological and Molecular Plant Pathology*, vol. 117, p. 101781, 2022. <https://doi.org/10.1016/J.PMPP.2021.101781>
- [22] P. Jha, D. Dembla, and W. Dubey, "Deep learning models for enhancing potato leaf disease prediction: Implementation of transfer learning based stacking ensemble model," *Multimedia Tools and Applications*, vol. 83, no. 13, pp. 37839–37858, 2024. <https://doi.org/10.1007/S11042-023-16993-4>
- [23] M. Ashikuzzaman, K. Roy, A. Lamon, and S. Abedin, "Potato Leaf Disease Detection By Deep Learning: A Comparative Study," *Proceedings - 6th International Conference on Electrical Engineering and Information and Communication Technology, ICEEICT 2024*, pp. 278–283, 2024. <https://doi.org/10.1109/ICEEICT62016.2024.10534467>
- [24] R. Mahum, H. Munir, Z.U.N. Mughal, et al., "A novel framework for potato leaf disease detection using an efficient deep learning model," *Human and Ecological Risk Assessment: An International Journal*, vol. 29, no. 2, pp. 303–326, 2023. <https://doi.org/10.1080/10807039.2022.2064814>
- [25] C.C. Bonik, F. Akter, M.H. Rashid, and A. Sattar, "A Convolutional Neural Network Based Potato Leaf Diseases Detection Using Sequential

- Model," *2023 International Conference for Advancement in Technology, ICONAT 2023*, p. 2023.  
<https://doi.org/10.1109/ICONAT57137.2023.10080063>
- [26] J. Chen, X. Deng, Y. Wen, W. Chen, A. Zeb, and D. Zhang, "Weakly-supervised learning method for the recognition of potato leaf diseases," *Artificial Intelligence Review*, vol. 56, no. 8, pp. 7985–8002, 2023.  
<https://doi.org/10.1007/S10462-022-10374-3/FIGURES/6>
- [27] S.M. Alhammad, D.S. Khafaga, W.M. El-hady, F.M. Samy, and K.M. Hosny, "Deep learning and explainable AI for classification of potato leaf diseases," *Frontiers in Artificial Intelligence*, vol. 7, p. 1449329, 2024. <https://doi.org/10.3389/FRAI.2024.1449329/BIBTEX>
- [28] G. Huang, Z. Liu, L. Van Der Maaten, and K.Q. Weinberger, "Densely Connected Convolutional Networks," *Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4700–4708, 2017.  
<https://doi.org/10.1109/CVPR.2017.243>
- [29] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.  
<https://doi.org/10.1109/CVPR.2016.90>
- [30] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," p. 2017. <https://doi.org/10.1109/CVPR.2017.195>
- [31] K. Simonyan and A. Zisserman, "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION," *Computer Vision and Pattern Recognition*, p. 2015.
- [32] Jayadeva, R. Khemchandani, and S. Chandra, "Twin support vector machines for pattern classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 5, pp. 905–910, 2007.  
<https://doi.org/10.1109/TPAMI.2007.1068>
- [33] M.A. Chandra and S.S. Bedi, "Survey on SVM and their application in image classification," *International Journal of Information Technology (Singapore)*, vol. 13, no. 5, pp. 1–11, 2021.  
<https://doi.org/10.1007/S41870-017-0080-1/TABLES/1>
- [34] D. Lopez-Bernal, D. Balderas, P. Ponce, and A. Molina, "Education 4.0: Teaching the Basics of KNN, LDA and Simple Perceptron Algorithms for Binary Classification Problems," *Future Internet 2021, Vol. 13, Page 193*, vol. 13, no. 8, p. 193, 2021. <https://doi.org/10.3390/FI13080193>
- [35] J. Hu and S. Szymczak, "A review on longitudinal data analysis with random forest," *Briefings in Bioinformatics*, vol. 24, no. 2, pp. 1–11, 2023. <https://doi.org/10.1093/BIB/BBAD002>
- [36] A. Ibrahim Ahmed Osman, A. Najah Ahmed, M.F. Chow, Y. Feng Huang, and A. El-Shafie, "Extreme gradient boosting (Xgboost) model to predict the groundwater levels in Selangor Malaysia," *Ain Shams Engineering Journal*, vol. 12, no. 2, pp. 1545–1556, 2021.  
<https://doi.org/10.1016/J.ASEJ.2020.11.011>
- [37] "Plant Village Dataset,"
- [38] Ş. Aykat and S. Senan, "Derin Öğrenme Kullanılarak Fundus Görüntülerinden Katarakt ve Diyabetik Retinopati Tespiti," *Mühendislik Bilimleri ve Araştırmaları Dergisi*, vol. 5, no. 2, pp. 312–324, 2023.  
<https://doi.org/10.46387/BJESR.1332567>

University in 2024, still continues his duty in the same department. Dr. Aykat's work focuses on artificial intelligence, image processing and data mining.

## BIOGRAPHY



**Şükrü Aykat** was born in Midyat district of Mardin. After completing his high school education in Midyat, he graduated from Fırat University Faculty of Technical Education in 2004. He completed his master's degree at Van Yüzüncü Yıl University, Department of Computer and Instructional Technologies in 2017 with his thesis titled "Examination the Views of Vocational High School Teachers, Students and Managers About Interactive Board Before and After In-Service Training". He completed his doctorate in Istanbul University-Cerrahpaşa Department of Computer Engineering in 2023 with his thesis titled "Retinal Disease Detection From Optical Coherence Tomography Images Using Deep Learning". Aykat, who was appointed as an assistant professor of Computer Engineering at Mardin Artuklu