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Research Paper

Elma Yaprağı Hastalıklarının AlexNet Kullanılarak Derin Öğrenme Tabanlı Sınıflandırılması

Deep Learning Based Classification of Apple Leaf Diseases Using AlexNet

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Abstract— The diagnosis of a disease on the plants is a critical step in avoiding a significant loss of harvest and agricultural product amount. The indications can be found on parts of plants such as fruits, leaves, lesions, and stems. The leaf demonstrates the symptoms by changing, and therefore revealing the spots on it. This disease identification is accomplished through manual inspection for pathogen detection, which might take extra time and cost. Hence, automatic detection of plant diseases can be vital in the agricultural economy. This study proposes the use of a simple deep learning model, AlexNet, for detecting anomalies in apple leaves in order to predict the presence or absence of a disease in a tree correctly. The Convolutional Neural Network model is implemented using the Plant Village dataset, augmented to 12,624 images for proper training. The proposed apple leaf disease categorization system achieves an overall accuracy of 99.56 percent. For comparison of results, a different method, namely Binarized Statistical Image Features (BSIF), is also implemented. Furthermore, the results are juxtaposed against studies using similar state-of-the art approaches.

Keywords : *Apple leaf diseases, detection, deep learning.*

1. Introduction

The United Nations Food and Agriculture Organization projected that as much as 40 percent of farm crops are lost each year as a result of plant diseases. This has an impact on food security and agriculture, which are the primary source of income for some rural areas. This results in yearly agricultural trade losses of above $220 billion and leads to hunger for millions of people (Yan et al., 2020). It is important to set up policies and combat this problem. Traditionally, trained professionals can inspect plant tissues' leaves. This procedure necessitates extensive professional knowledge, yet the accuracy is low, and the disease may be identified wrongly (Dutot et al., 2013). With the evolution of machine learning techniques, experts have researched automating plant diseases detection and identification based on machine learning models as well as other techniques such as Support Vector Machine (SVM) and k-Nearest Neighbors to increase the accuracy of the results (Es-saady et al., 2016; Sannakki et al., 2013; Qin et al., 2016; Rothe & Kshirsagar, 2015; Wang et al., 2017).

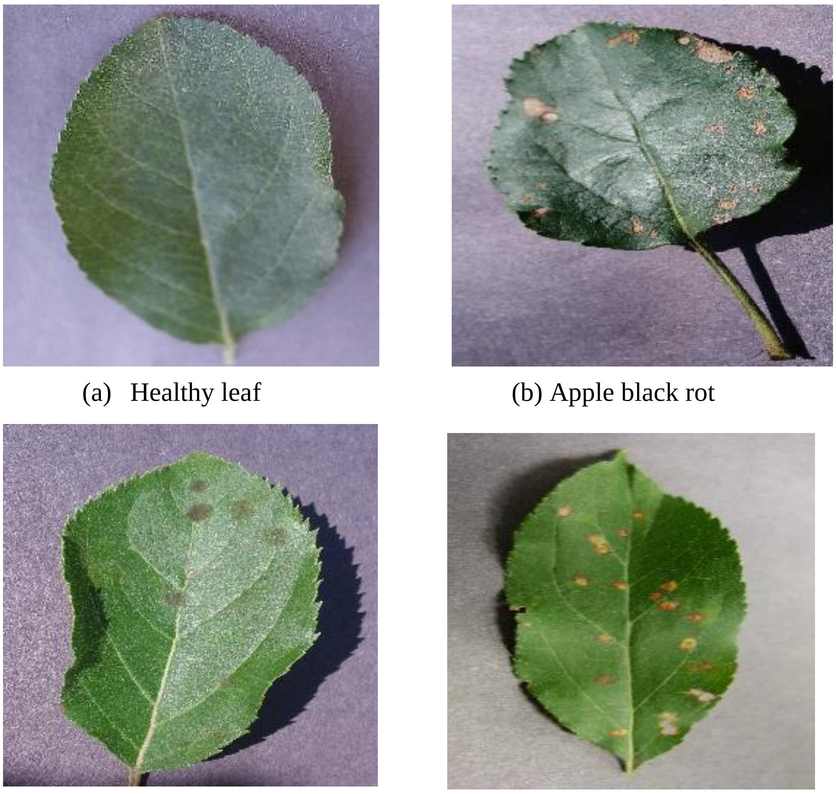
Using the PlantVillage dataset, this study seeks to properly identify and classify diseases in apple leaves using a modified Convolutional Neural Network (CNN) architecture, namely AlexNet, and compares the outcome of the proposed approach with those obtained from a texture-based technique, namely BSIF. There are almost 50,000 professionally gathered images and 38 classes in the Plant Village dataset. This collection is made up of various plant leaves with distinct symptoms. The plant researched in this study from Plant Village dataset is the apple.

1.1. Significance of the Study

This study utilizes a convolutional neural network to identify and characterize apple leaf diseases. Correctly diagnosing apple leaf diseases can significantly cut loss for orchard farmers while also lessening the burden on experts who must undertake manual checks. Besides, it can help orchard farmers make sound decisions about how to protect other plants from contagious diseases.

1.2. Apple Leaf Diseases Symptoms

Pathogens such as fungus, bacteria, and viruses are responsible for diseases in apple leaves. When these viruses get access to the tree through natural cracks or wounds, they spread and negatively impact the tree's leaves and fruits. Apple leaves are frequently attacked by fungus spores. Wind, rain, and the movement of insects, animals, and equipment can all disseminate the spores. Apple scab, cedar apple rust, apple black rot, fire blight, and other diseases harm apple leaves. Figure 1 shows the types of apple diseases identified in this study.



(a) Healthy leaf (b) Apple black rot

(c) Apple scab leaf (d) Apple cedar rust

Figure 1. Samples of healthy and diseased apple leaves

The apple scab disease causes brown patches on the leaves. The leaves are usually dark green or brownish in color and range in size. The fungus venturia inaequalis causes this disease, which is one of the most frequent and destructive leaf diseases in apple trees.

Cedar apple rust emanates from the fungus Gymnosporagum juniperi-virginianaea. It belongs to the fungus family Pucciniaceae. When orange-brown tendrils with cedar tree spores fall on the apple trees' leaves, fruit and twigs, they germinate and penetrate the tree's surface, causing small yellow-green patches on the top surface of the leaves and orange-brown pustules on the lower surface. The spots may become larger as the illness continues and the leaves may turn yellow and fall off prematurely, reducing the fruit's marketability.

Apple black rot is a fungus caused by Botryosphaeria obtusa that attacks apple trees. It causes the leaves to turn yellow and eventually brown in colour, as well as black patches on the fruit. The fungus can infect the tree's twigs, branches and trunk, generating cankers. Black rot can also cause the fruit to decay either when it is on the tree or after picking. This fungus spreads swiftly in damp areas.

The following sections are listed in the subsequent order: The second section is a synopsis of similar works. The methodology proposed in this study is given in the third section, while the third section presents the experiments carried out along with their results and the comparison of the results with other studies. Finally, section 5 presents the study's conclusion.

2. Related Works

Apple leaf disease classification is studied in the literature using deep learning and hand-crafted methods. However, recent studies are concentrated on deep learning approaches. Liu et al. (2018) used a deep convolutional neural network to treat mosaic, rust, brown spot, and alternaria leaf spot in apple leaves. Based on the AlexNet model, the authors create an architecture for a deep convolutional layer. They used a dataset of 13,689 images of damaged apple leaves. The experimental results demonstrate that their proposed disease identification approach achieves an overall accuracy of 97.62% in the hold-out test set. By breaking down the convolutional kernel, modernizing the identity mapping approach, lowering the amount of residual modules, and swapping out the batch normalization layer, Yu et al. (2022) suggested a multi-step optimization ResNet apple leaf disease recognition model based on the ResNet50 network.

Fu et al. (2022) proposed a lightweight convolutional neural network (CNNs) based on the AlexNet model for five diseases (Alternaria blotch, brown spot, gray spot, mosaic and rust) affecting apple tree leaves. Dilated convolution is used in the model to extract dense disease traits, which helps to maintain a large receptive field while minimizing the number of parameters. In comparison to five other models, their model design is acceptable and resilient. Additionally, the suggested model has a high accuracy of 97.36 percent in identifying apple leaf diseases.

The use of image processing and machine learning has also been suggested as a tool for effectively detecting both Cedar apple rust and black rot diseases (Chakraborty et al., 2021). The methodology detects healthy apple leaves, and in the case of any diseased leaves, it identifies it and gives an exact percentage of the disease-infected area. Authors use a total of 500 images. For every image, 10 features were extracted using the Gray-level Co-occurrence matrix (GLCM) algorithm and they constructed a multiclass SVM model. The proposed method yields an accuracy of 96 percent.

Meyyappan and Chandramouleeswaran (2018) outlined the key image processing techniques used for identifying leaf diseases, which are k-means clustering and SVM. They found that this method can greatly aid in the accurate diagnosis of plant disease and can help farmers to recognize the affected area of leaf and distinguish the illness accurately; hence the user can rectify the situation incredibly easy and at a low cost. Alqethami et al. (2022) aimed to detect and prevent the spread of apple leaf diseases at their early stages. To accomplish this, 240 images were gathered and classified as healthy or diseased. To increase image quality, the images were pre-processed, and the Local Binary Pattern (LBP) approach was employed to extract features from region of interest of the image segmented from the original image to exclude background and other unnecessary parts. CNN, SVM, and KNN were used as prediction models. The accuracies of the three models are 98.5%, 82.25%, and 70.3%, respectively.

3. Methodology

In this study, to detect and classify diseased apple leaf images correctly, four main steps are implemented which are acquisition, pre-processing, feature extraction and classification as shown in Figure 2. The training phase and the testing phase are typically the two steps in the classification of plant diseases. Deep learning based approaches perform feature extraction and classification together, however, hand-crafted methods perform each step separately. In the implemented hand-crafted method in this study, the training phase extracts the features of the image. In the testing phase, the features of the test image are extracted and using the Nearest Neighbor classifier with the Manhattan distance, the test image is classified based on the comparison with the extracted features obtained from the training phase.

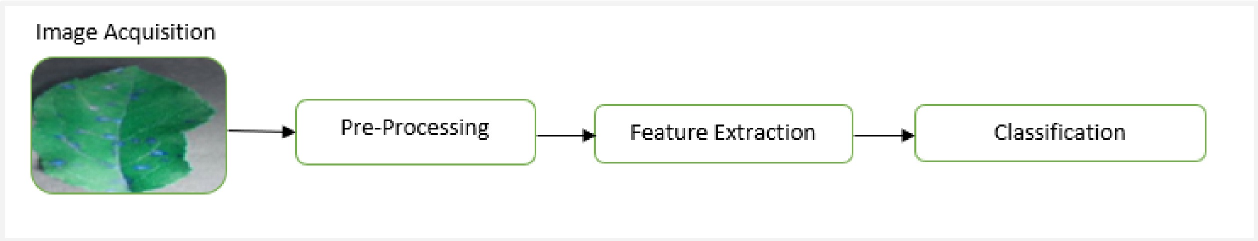


Figure 2: Overview of Apple Leaf Classification

3.1. Acquisition

Since the features used to train the system are extracted from the acquired images, this stage of the system definition is crucial. The recovered features will stand out from those of other classes if there is a good collection of photos with distinct different qualities, enhancing the classifier's discriminating power. The IPM dataset, PlantVillage dataset, and APS dataset are all popular plant disease detection databases. Self-acquired images utilizing a hyperspectral imaging device are another source of images. To get images with desirable qualities like orientation and continuous illumination, they are taken in a lab or using a sample box.

3.2. Pre-processing

Depending on the purpose of the identification system being developed, several pre-processing methods are used. The pre-processing technique used in this study is the conversion of colored images to grayscale. Converting the image to grayscale reduces the computational load because grayscale images have only a single channel as opposed to three channels like a colored image. Removing the colors eliminates color dependent features which allows the algorithm to focus on texture, shape and other important image features.

3.3. Feature Extraction

Feature extraction in this study is done using AlexNet CNN model, AlexNet rose to fame after winning the Imagenet Large Scale Visual Recognition Challenge, a yearly competition that assesses methodologies for large-scale object recognition and image categorization. AlexNet has a total of eight layers as shown in Figure 3. The model is fed an image with dimensions of 200 x 200 x 3. There are five convolutional layers and three fully connected layers in total. Following each layer is a Batch Normalization Layer and a ReLU activation. Following the first two convolutional layers is an overlapping Max Pooling layer. The third, fourth, and fifth layers are all directly related. Following the fifth convolutional layer comes a Max-pooling layer, which is coupled to the fully connected layer. To avoid overfitting, the fully connected first and second layers each have a neuron of 4096 followed by a batch normalization layer, ReLU activation, and a dropout layer of 0.5 (Krizhevsky et al., 2017, Babalola et al., 2020). Finally, the output layer has four neurons because the data set has four classes using Softmax activation function.

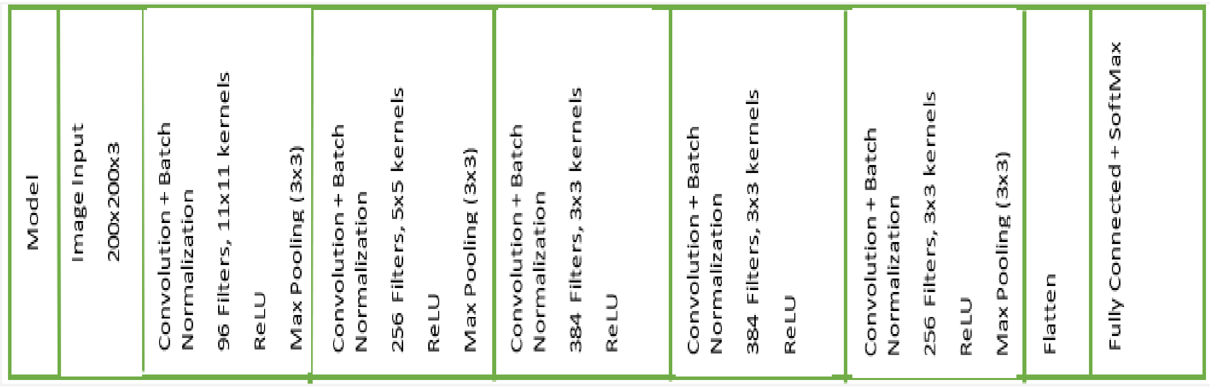


Figure 3. AlexNet Architecture

3.4. Feature Extraction

This is the penultimate stage in the categorization and identification of leaf diseases. At this point, test leaves must be categorized into their respective categories. Support Vector Machines (SVM), K-Nearest Neighbor (K-NN), Rain forest algorithm, Linear Discriminant Analysis (LDA), Neural Networks, and other techniques are used to implement classification of plant leaf diseases. These classifiers can be classified as either supervised, unsupervised, or semi-supervised machine learning methods. In this study, the distance between the trained and test images is calculated using the K-Nearest Neighbor Classifier using Manhattan distance. The distance value indicates the proper class to which the sample image belongs. In this study, k is set to 4 corresponding to the four classes of apple leaves present in the dataset.

4. Experiment and Results

4.1. Dataset

The Plant Village dataset was utilized as the basis for this analysis. Because apple leaves are the major emphasis of this study, the colored set of these are used. The original data collection contains a total of 3171 images. The categories of apples leaves in the dataset includes, healthy apple, apple scab, apple black rot and apple cedar rust each include 1645 images, 630 images, 621 images and 275 images, respectively. The initial dataset in Table 1 is small and could potentially lead to overfitting. To prevent this, data augmentation techniques are carried out on the dataset.

Table 1. Initial dataset distribution

Class	*Total Images*	*Training (60%)*	*Validation (20%)*	*Test (20%)*
Apple black rot	621	373	124	124
Apple cedar rust	275	165	55	55
Healthy apple	1645	987	329	329
Apple scab	630	378	126	126

4.2. Data Augmentation

The enhanced data is created by making slight adjustments to the original data. The data augmentation techniques employed in this study are 0-10 rotation range, 0- 0.15 shear range, rescale of 1./255, 0.05 and 0.02 ranges for width shift and height shift, respectively, and 0.2 zoom range.

For each class, 3156 images were generated. The new training set becomes 1894 images for every class, the new validation and testing set becomes 631 images for every class. In total, the training set consists of 7576 images, the testing and validation set contains 2524 images in total and all the number of images aforementioned are shown in Table 2.

Table 2. Dataset distribution after augmentation

Class	*Total Images*	*Training (60%)*	*Validation (20%)*	*Test (20%)*
Apple black rot	3156	1894	631	631
Apple cedar rust	3156	1894	631	631
Apple healthy	3156	1894	631	631
Apple scab	3156	1894	631	631

4.3. Results of Experiments

The proposed model was trained over 50 epochs, using SGD optimizer with 0.001 learning rate. Figure 4 depicts the proposed model's confusion matrix on the test-set. From the diagram, labels 0 through 3 represent the 4 classes in this order; 'apple black rot', 'cedar apple rust', 'apple healthy' and 'apple scab'. The number of correctly predicted images for each of the four classes is shown in Figure 4. The apple black rot class and the cedar apple rust class are both 100 percent accurate, the apple healthy class is 98.57 percent accurate, and the apple scab class is 99.68 percent accurate.

From the confusion matrix shown in Figure 4, the accuracy for the system can be calculated as:

$$\text{Accuracy} = \frac{Number\ of\ correctly\ identified\ images}{total\ number\ of\ images} * 100 \quad (1)$$

Based on the equation (1), the model's accuracy on the test image is found to be 99.56%.
Aside from using the confusion matrix to examine the accuracy of the model, the f1-score, precision, and recall are also calculated as shown in Table 3. The other performance metrics used in this study can be defined as follows:

- Precision is defined as the percentage of accurately predicted positive outcomes out of all positive outcomes forecasted.
- The fraction of accurately predicted actual positives is determined by recall.

- The f1-score is the weighted harmonic mean of recall and precision. The best possible f1-score is 1.0, while the poorest possible f1-score is 0.0.

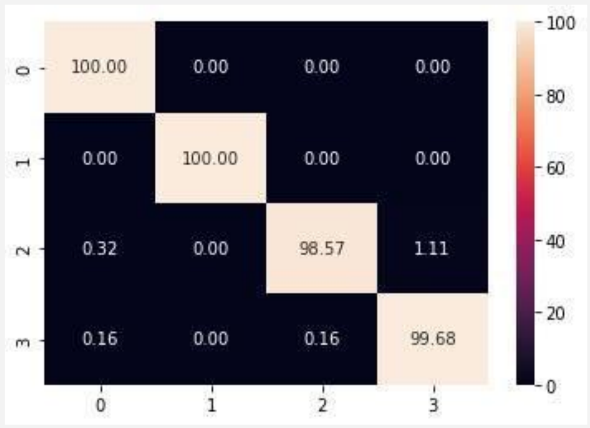


Figure 4: Confusion Matrix

Table 3. Proposed Model Classifier Performance with Different Metrics

Metrics	Precision	Recall	F1-score
Performance	0.9956	0.9956	0.9956

Table 4. Result of BSIF on Initial Dataset

Filter Size	**Initial Dataset Accuracy (%)**	**Augmented Data Accuracy (%)**
17x17_12 bits	87.68	99.77
15x15_12 bits	88.73	99.68
13x13_12 bits	88.52	99.65
11x11_12 bits	88	98.86
9x9_12 bits	87.16	97.86
7x7_12 bits	84.21	94.35
5x5_12 bits	78.94	85.34

4.4. Comparison of Related Works

Another experiment was run using BSIF as a comparative. This is an image description that is derived from a image's textural characteristics. Utilizing Independent Component Analysis, the method trains a number of filters using real-world images. Binary strings are created from the neighbors of pixels in an image. Various filters result in various sets of code. Binarizing the resulting code allows it to be utilized as image descriptors. The binarized statistical image feature's histogram of each pixel's binary code serves as the image's representation. The code that binarizes the image coordinates is created using component analysis and thresholding. The pixel neighbors of an image are binarized in BSIF using filters created from a small number of images; different filters are used for different applications of the approach, and they yield bit string features of different lengths. The binarized output codes serve as a representation of the candidate image's textural components, which are derived from the neighborhood's intensity distribution. By splitting a image into 8 by 8 pieces, one can obtain the feature vector representation of the image. The global description of the image is created by concatenating the descriptors generated in each region (Kannala & Rahtu, 2012).

Several BSIF filter sizes of 12 bits were employed to get the accuracy on the colored apple leaf images. The 12-bit filter size is selected because it finds a balance between the quantity of information captured by the filter and the algorithm's processing performance. A larger filter captures more information but requires more processing resources. A smaller filter captures less information but is more computationally efficient. This means the filter is resistant to noise and fluctuations in illumination, making it well-suited for real-world applications.

Table 4 shows that the result with the 15x15_12 bits produced the highest accuracy, accounting for 88.73% while 17x17_12 bits produced the highest accuracy of 99.77% with the augmented dataset. The accuracy is calculated with the formula shown in equation (1).

Details of related research on apple leaf disease categorization using CNN models, including the model employed, the apple classes, number of images used, dataset used and accuracy are summarized in Table 5.

Table 5. Comparison of Different CNN Models on Apple Leaves

Study	Model	Specie Classes	Number of Images	Accuracy (%)
Yu et al. (2022)	AlexNet	Mosaic, Rust, Brown spot, and Alternaria leaf	13,689	97.62
Liu et al. (2017)	MSO-ResNet	Healthy leaves, rust, scab, Powdery mildew, Alternaria spot, and Alternaria spot and rust,	11,397	95.80
Yu et al. (2022)	VGG16	Apple black rot and Apple Healthy	1644 healthy leaves, and 442 diseased leaves at three stages.	90.40
Sannakki et al. (2013)	Modified VCG16	Healthy, scab, forgeye apot, cedar rust	2141	99.01
This Study	AlexNet	Scab, black rot, cedar rust, and healthy leaf.	12,624	99.56

5. Conclusion

Apple leaf diseases are classified in this study using a CNN model, namely AlexNet. The algorithms are applied to the apple class in the Plant Village dataset, which includes 4 classes of apple leaves with 1645 healthy apple images, 630 apple scab images, 621 apple black rot images and 275 apple cedar rust images. Data augmentation is used on the database resulting in a total of 12,624 images. The method has a 99.56% overall accuracy. Precision, recall, and the F1-score are all computed. A confusion matrix was obtained in addition to the performance metrics. Apple black rot and apple cedar rust are both classified as 100% accurate, apple healthy is 98.58% accurate, and apple scab is 99.68% accurate.

For comparison, a hand-crafted feature extraction method namely Binarized Statistical Image Features is also implemented and the results are juxtaposed with the results obtained from the proposed method. The suggested method is further contrasted with state-of-the-art approaches to demonstrate that, when compared to state-of-the-art outcomes, the proposed method achieves greater accuracy in classifying apple leaf illnesses.

On the other hand, several plants can be examined in the future with an interface for farmers which will be developed to achieve the maximum food security that the humankind deserves. Additionally, other deep learning and hand-crafted methods and methodologies can be studied for the identification and designation of diseases on apple leaves. Moreover, multiple diseases on the same plant leaves can be studied and classified in futher studies.

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