Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 7, S. 251-259, 10, 2023

Araştırma Makalesi

IJANSER

https://alls-academy.com/index.php/ijanser
ISSN: 2980-0811

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 7, pp. 251-259, 10, 2023

Research Article

Real-Time Apple Disease Detection and Classification Using Hybrid CNN Model

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(Received: 05 November 2023, Accepted: 13 November 2023)

(2nd International Conference on Contemporary Academic Research ICCAR 2023, November 4-5, 2023)

ATIF/REFERENCE: Rafay, A., Aqeel, M., Iqbal, M., Sohaib, A., Islam, B. & Zaheer, A. (2023). Real-Time Apple Disease Detection and Classification Using Hybrid CNN Model. *International Journal of Advanced Natural Sciences and Engineering Researches*, 7(10), 251-259.

Abstract – Identifying and categorizing diseases in apple fruit is a difficult and time-consuming task in the field of agriculture. It is crucial to have an automated method for detecting apple diseases to effectively monitor and ensure sufficient and healthy production. While disease symptoms are visible in the apple fruit, having experts diagnose them in a lab is expensive and time consuming. This paper proposes a deep learning approach to detect and classify three types of common fungal diseases in apples (apple scab, apple rot, and apple blotch) from Red Green Blue (RGB) images of apples taken at various resolutions. The convolutional neural network model is used to distinguish between healthy and diseased apples. Agriculture heavily relies on digital image processing and analysis to ensure the production of high-quality fruits. Using CNN as a classifier to automatically detect and classify apple diseases, we have experimentally proven the importance of pre-programmed knowledge in the agriculture industry. Cross-validation and testing on unseen data were conducted to exhaustively evaluate the trained model in various parameters. The experimental results have demonstrated that the proposed deep learning-based algorithm can accurately classify the three types of apple diseases with good accuracy.

Keywords – CNN, Machine Learning , Apple Disease Detection, Classification, RGB Images

I. INTRODUCTION

Apple fruit is significantly impacted by various diseases, affecting agriculture industries and production globally. Compared to the potential apple production, the average national apple yield is relatively small [1]. The primary causes of the low apple production include adverse environmental variables, inadequate post-harvest technology, inadequate basic research, and a lack of sufficient availability of high-quality planting materials to farmers. The most common diseases that affect apples are Bloch Apple, Rot Apple, and Scab Apple. Therefore, it is essential to properly care for apples by using fertilizers [2]. The farmers can be helped, and future losses can be avoided by taking the appropriate steps in response to an early detection of such problems in the apples. Farmers sometimes miss the ideal time for preventing such diseases by relying only on conventional methods for identifying plant diseases [3]. The lack of automation causes a decline in the quality of fruits and crops. Technology development has led to the development of machine learning and other soft computing techniques, which are particularly helpful in Apple's automatic illness identification and categorization [4]. The extracted features were subjected to a variety of machine-learning techniques, and the resulting model had a 94% accuracy rate. An evident advantage of deep learning over machine learning is that deep learning techniques can be used directly to raw data in various forms such as jpeg. This can improve the overall effectiveness of disease analysis in Apple. However, feature extraction, a further preprocessing step, is necessary for machine learning. Any impurity in the data might cause the model to train incorrectly during deep learning, which will result in an inaccurate classification of the data.

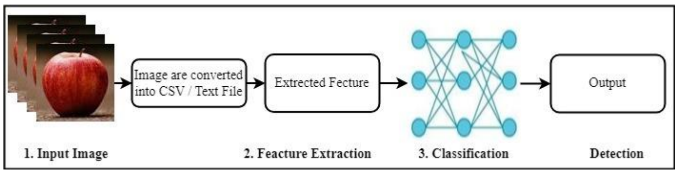

Figure 1. Basic machine learning process steps

Making feature extraction unnecessary is the main benefit of applying deep learning techniques. It is imperative to possess a thorough comprehension of the problem at hand to successfully extract features. Deep learning techniques extract high-level characteristics incrementally from the data. The processes of feature extraction and classification are combined in deep learning. Convolutional neural networks are being used because of developments in computer vision and deep learning (CNNs) [5]. For image classification applications, CNNs have emerged as the standard models. Its architecture and the way characteristics are extracted and sent to the following levels are by far its greatest advantages. CNN typically consists of two modules. It includes the extraction and classifier modules. By using convolution and pooling, the feature extraction module's job is to extract the important features from the picture. The classifier module uses the retrieved characteristics to conduct its output prediction function. demonstrates a convolutional neural network's reduced form. Since 2016, Numerous researchers have initiated the utilization of Convolutional Neural Networks (CNNs) to capitalize its potential to develop enhanced image classifiers. In their study, Srinidhi et al. analyzed 19 distinct research that used CNNs to automatically identify ailments in Apple [6]. Their analysis also reveals the serious flaws and problems with this research. We attempted to make use of CNN's capability for our study while keeping in mind how well it performs as a classifier for picture data. In this study, we suggested an ensemble of cutting-edge deep learning models to automatically identify four types of diseases in apple leaves: healthy, scab, rust, and multiple disorders. We applied transfer learning to transfer the previously discovered models' information into our study. On the validation dataset, our suggested model had a 96.25% accuracy rate. According to the results, the model performed better than several other earlier models that had been put out in terms of its performance criteria, such as accuracy, etc. Additionally, a web application is used to implement the suggested model, making it available to farmers [7].

The success of the global apple industry is a result of its cultivation, efficiency, and high demand. The quality of the harvest is crucial for achieving economic development. The quality of apples can be seriously affected by different diseases. This can have a significant impact on the agricultural economy. So, the detection of apple diseases in the early stages is important for agriculture loss and to promote economic development. We aim to develop a system that helps us and classifies diseases. we are developing a web-based application for Apple disease detection And Classification using deep learning. The image of the apple will be uploaded as an input to the system and the image will be further processed using CNN Model [8]. We are using trained datasets and then the image classification is done using machine learning which will detect the disease of apple. The main algorithm used in the system is CNN (Convolution Neural Network). All the systems would be implemented using Python Language. In this paper, we present an assessment and suggestion for detecting apple diseases using images. The project consists of several steps. Firstly, the apple images are segmented using clustering techniques. Secondly, features are extracted from the input images. Finally, the diseases are classified through the use of a CNN model. [9]. To validate the proposed model, four types of apples were tested - those with blotch, rot, scab, and normal. The results showed accurate disease detection. This innovative online platform empowers farmers to identify potential crop diseases at an early stage, thereby mitigating losses and enhancing economic gains for the agriculture sector [7].

II. RELATED WORK

Li et al. [10] proposed a novel method for apple quality identification using CNN, Google inception model v3 model. Three methods are followed in this model, CNN, Google inception model v3, and traditional imaging process methods like SVM. They were trained to identify the quality of apples. The best accuracy obtained from the Google inception method in training and validation was 92% and 91.2% respectively. This model took a short time to train. These three methods were tested independently and provided accuracy of approximately 95.33%, 91.33%, and 77.67%, respectively. It was only detecting the quality of apples and with size, color, and type. Gaikwad et al. [11] proposed the paper, their focus was to detect the diseases of apples through the images of apples. The convolution neural network (CNN) model is based on the trained dataset of the dataset. The path of images is given, needs to run code and the system will be able to predict the disease of apple that is suffering. The fine-tuning that CNN models make in the changes of the parameters in the values of dropout, size in the batches, training, and testing split. The accuracy that is best in the model is 98.41%, the accuracy of the rotting apple is 98.71%, the accuracy of the scab is 99.7%, the accuracy of blotch is 98.70% and the healthy apple is 97.3%. Ayaz et al [12] proposed a technique for categorizing and identifying apple illnesses based on image processing. It is composed of mainly three steps; image segmentation is first performed using the K-means clustering technique. In the second step, feature extraction is performed from the images of the apples. In the third step, classification and training are performed using a learning vector quantization neural network (LVQNN). In this paper, there are only three diseases detected and classified using K-means clustering named: Apple blotch, Apple scab, and Apple rot. The experimental results of the apple fruit disease detection using the K-means clustering technique are approximately 95% of the rate of the algorithm. Abhijeet et al. [13] proposed a methodology and developed for the recognition and classification after a most extensive and broad literature survey. Three main deep-learning models were selected after keeping in view their performance and previous work. These three models were CNN, ResNet50, and VGG16. The focus of this research is to investigate how deep learning models can interact with large datasets across various categories and improve image segmentation. The goal is to enhance performance and ensure high quality across a broad range of categories. The performance of two deep learning models, VGG16 and CNN, was like the rest of the models, ResNet50, but they did not perform well on large verities of fruits when employed on the augmented images.

(Recognition and Classification of Fruits using Deep Learning Techniques n.d.) [14] proposed a methodology that requires access to data before researching apple diseases. The availability of relevant training data is crucial for accurately detecting these diseases. Unfortunately, there is a limited number of datasets available online. This poses a challenge for both the agricultural industry and apple plantations. However, it's still a viable option. There is improvement in the existing model and various CNN models have emerged. Their focus is to make the detection model more efficient for disease detection of apples.

According to the research conducted in [7], the industry demands technological solutions focused on automating agriculture tasks for increasing production and profit which reduces the time and cost. This technology is based on an image processing system and solved many problems and challenges.

Jiang et al. [15] stated that to ensure the healthy development of the apple sector, current research lacks a reliable and quick detector of apple disease. For the real-time identification of apple diseases, deep learning is used in combination with an upgraded convolutional neural network (CNN). The collection for apple disease includes complicated images captured in the field and laboratories.

Jiang et al. [16] proposed a model to measure the quality of the apples and their characterization of apples which determine the infection of apples. The model also determines the apples that are infected and non-infected based on input images which classifies the infected apple as level of average, medium, and high.

Sood et al. [17] proposed and evaluated based on image processing the solution to the problem of apple disease detection. It is composed of basically three steps. The first step is performed for the defect segmentation using the K-means clustering technique. Features extracted in the second step. The third step is performed on Multiclass SVM for the training and classification. These steps are performed for the identification of three diseases, apple rot, apple scab, and apple blotch.

Dubey et al. [18] developed a solution based on the image processing proposed which is more efficient for the detection and classification of apple diseases. This approach is mainly composed of three steps for apple disease detection. The first step is performed by image segmentation using a technique called K-means clustering techniques. The features are extracted from the input image in the second step. There are training and classifications that are performed by using SVM. Their focus was to promote the farmers by doing smart work. The goal is to increase the value of apple crops by making informed decisions and reducing losses due to disease.

Marandi and Chakravorty [19] proposed and evaluated a process of image processing for detecting fruit disease of apple using deep learning which will show testing and accuracy of apple fruit. Subclasses VM and CNN have separated apples into healthy and unhealthy categories. The quantity of training and testing epochs, the size of the batch, and the dropout had a higher impact on the corresponding outcomes.

III. MATERIAL AND METHOD

A. *Overview*

Our project is working with deep learning model CNN and machine learning. We have proposed and experimentally the significance of using the CNN Model for the automatic detection and classification of apple diseases. We have considered three types of diseases in apple fruit: apple blotch, apple rot, and apple scab. So, first, we input the dataset/image of our model and start the preprocessing step on it, During the preprocessing step image will be resized automatically. CNN model works on 4 layers: convolutional layer, pooling layers, ReLU layer, and fully connected layer. These layers are working in our model to perform apple disease detection. After the image is resized, the next step involved in the dataset is feature extraction. In the feature extraction technique, our model divides the dataset into four classes/categories and then extracts the feature. It means reading the dataset/image in pixels, checking all the pixels applying four layers of the CNN model for image classification to get better results in detection. Moreover, our project is working on machine learning and deep learning techniques. So, we apply the random forest classifier as a classification like the CNN model in testing data to get more perfect apple disease detection. Random forest classifier is a supervised learning technique. It can be used for classification, in this process combining the four diseases of apple to classify solving complex problems and to improve the performance of the model. Classification in the CNN model predicts the apple disease if the dataset is a diseased apple, then the model should predict the apple is diseased, further applying the whole dataset that we are input to our model for detection of disease. After that we get the prediction result or output of our model, then generate the performance/ accuracy confusion matrix and chart for the result of prediction/detection of apple disease. The user must submit an image of an apple with a disease for detection on our online application. The user is presented with the outcome after pressing the upload button, which sends the image to the backend where it is input into our model.

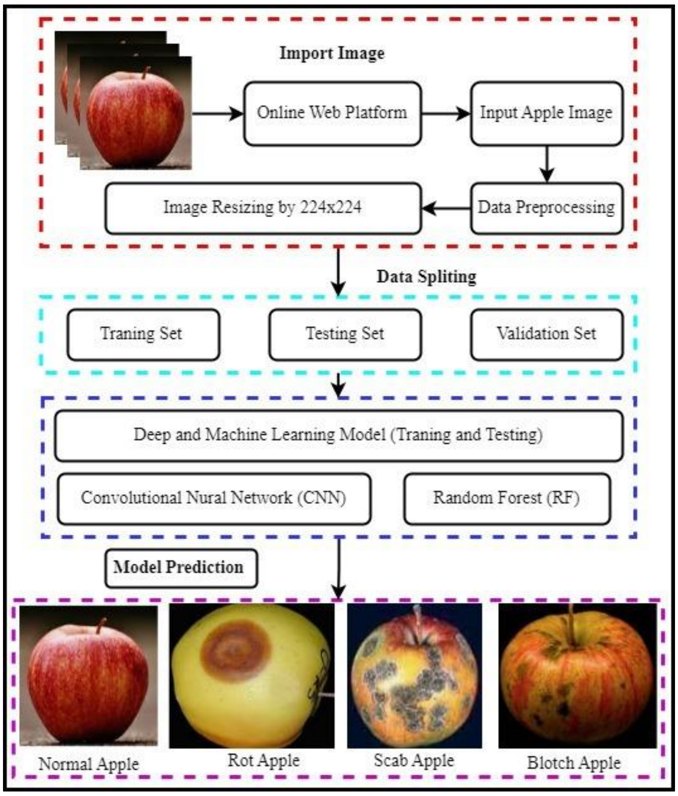

Figure 2. Block diagram of the proposed model.

B. Dataset Collection

A significant dataset to assess the suggested approach is one on apple disease. It is comprised of different real-world and region-based diseases which are apple scab, apple rot, and apple blotch. These diseases are selected because they have an insignificant impact on the growth of apples. The Kaggle dataset displays various real-world disease examples from the training and testing samples shown in Fig 3. The Kaggle dataset is publicly free available. A machine and deep learning technique that is extensively applied to apple image disease detection, 70% of apple images are used for training 20% of images are used for testing and 10% of apple images are used for validation. Our trained model achieved an average accuracy of 90% of our test dataset and the performance parameters are:

- False-Negative (FN): The image sample result is 0 and disease present in the image.
- True-Negative (TN): The frame result is 0 and disease is absent in the image sample.
- False-positive (FP): The image or frame result is 1 and disease is absent in the image sample.
- True-Positive (TP): The image result is 1 and disease is present in this frame.

For the suggested technique's validation, performance indicators like accuracy, specificity, and F1-score are computed. The computations made for the suggested technique's performance parameters are as follows:

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{3.1}$$

$$Recall = \frac{TP}{TP+FN} \tag{3.2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3.3}$$

$$F1 - score = \frac{2*(Recall*Precision)}{(Recall+Precision)} \tag{3.4}$$

C. Image Preprocessing

The Kaggle apple disease, the proposed strategy is tested and evaluated using a dataset. The region-based and real-world diseases are apple scab, apple rot apple blotch, etc. Because we know that videos are collections of frames, we have preprocessed and extracted features from the videos by turning them into frames. Video image conversion and image resizing are being implemented. The image resizing is very important because the dimensions of each video frame are not the same. The resized images are fed into the proposed model.

D. Classification

To categorize the many types of apple disease in the Kaggle dataset, two different effective classifiers RF and CNN used for the four classes used in the suggested strategy for classifying the apple illness. In the same example, each classifier provides its results as a disease type or normal. However, a majority vote system is used to make the final determination of the disease type or normal apple. The majority vote counts all four outputs, and the outcome is given as which output has a higher value. With the available literature, classification of the different disease categories produces better outcomes. Different classifiers perform the classification, and certain features are taken from the input and the disease image. The parameters of the conventional classifier are then compared to these features to determine the apple disease's final classification. The terms F1-score, precession, and accuracy refer to evaluation parameters. Each classifier's effectiveness ranges from 80% to 97%. When the majority decision is used in these classification procedures, the classification efficiency is comparable to that of the literature already in existence.

IV. EXPERIMENTATION AND RESULTS

The suggested approach is based on the CNN model, which is used to extract hidden properties like apple texture, patterns, and form from images. Machine learning classifiers are used to classify the type of apple disease classification. When compared to the other categorization methods already in use, the optical and parametric results demonstrated promising results in terms of accuracy. RF and CNN are compared and tested to the better classifier for apple disease detection. Following experimental validation, CNN was found to be a superior classifier for disease detection in images. CNN classifier is the most accurate among the four classifiers.

A. Random Forest

Random Forest (RF) is a supervised machine learning method used for classification. It creates a forest of random trees, where the number of trees directly affects the accuracy of the prediction. By implementing multiple trees, we can classify apple diseases, and each tree provides a specific classification. The forest then selects the classification that received the most votes from the individual trees. The three structures, max_features, n_estimators, and min_sample_leaf can be modified to increase the RF performance [20].

Table 1: Tested sample accuracy.

Random Forest			
Test Sample	**F1 Score**	**Precision**	**Accuracy**
Test-1	0.453	0.764	0.876
Test-2	0.605	0.874	0.892
Test-3	0.704	0.608	0.962
Test-4	0.453	0.764	0.876
Test-5	0.563	0.876	0.879
Test-6	0.637	0.931	0.892
Test-7	0.873	0.873	0.952
Test-8	0.694	0.837	0.959
Test-9	0.736	0.454	0.963
Test-10	0.878	0.547	0.982

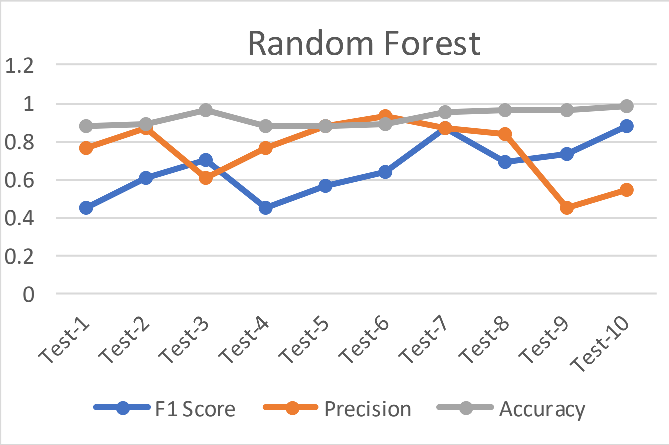

Figure 3. Performance parameter of RF.

B. CNN Model

CNN model has been used for apple disease detection and disease classification in an image. An image classification into one of the classes based on identifies the main disease. CNN input layer takes normalized data 224x224; the convolution layer involves 64 units and 2x2 kernel. After the convolutional layer, data goes through the pooling layer, which uses the 2x2 kernel. First compressed and then served into a fully connected layer. In the end, the output layer receives the input from other layers and compresses and converts the output into a different number of classes of apple disease. The first dense layer takes 128 units and a dropout rate of 0.43 and the second dense layer takes 64 units and a dropout rate of 0.33.

Table 2: CNN testing sample result.

Convolutional Neural Network Model			
Test Sample	**F1-Score**	**Precision**	**Accuracy**
Test-1	0.709	0.609	0.894
Test-2	0.504	0.709	0.973
Test-3	0.305	0.509	0.981
Test-4	0.609	0.896	0.982
Test-5	0.708	0.687	0.979
Test-6	0.406	0.876	0.991
Test-7	0.437	0.875	0.974
Test-8	0.609	0.984	0.983
Test-9	0.894	0.678	0.991
Test-10	0.437	0.875	0.974

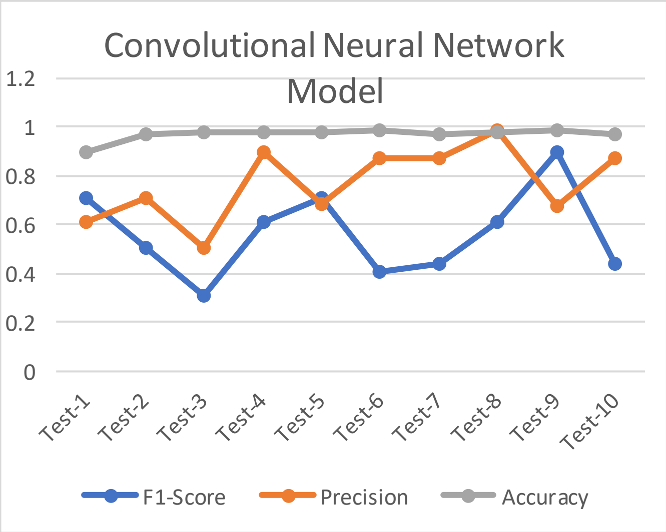

Figure 4. CNN Performance parameter results.

Table 3: Comparison of existing method.

Ref#	Disease	Method/Model	Accuracy
[13]	Apple scab	Multi-scale Dense Inception V4 With Cycle-GAN	93%
[15]	Fruits Recognition	Alex Net	95%
[16]	Rot, Mildew, and Scab	MobileNetV2 & CNN	96%
Our Work	Rot, Scab, Blotch	CNN & Random Forest	98%

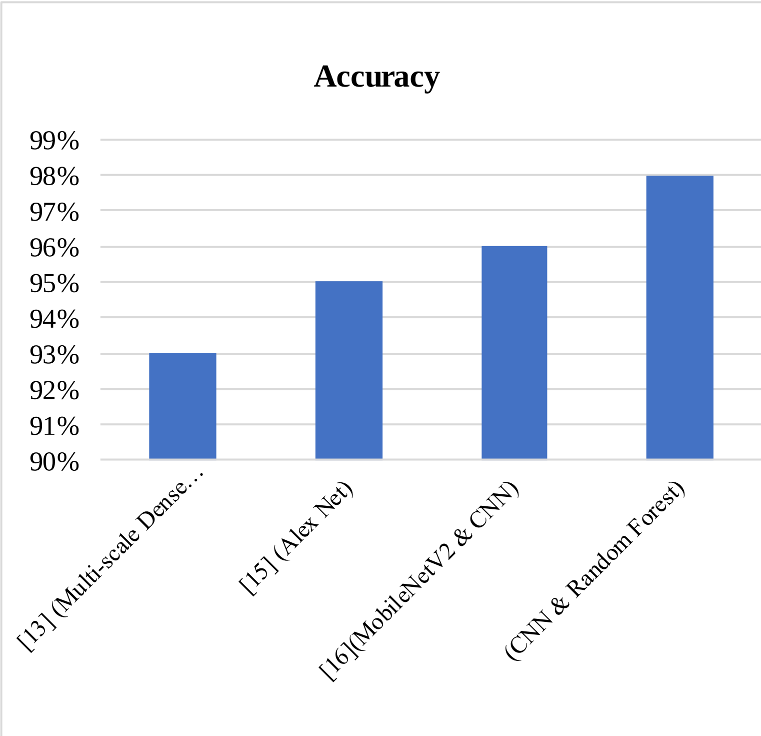

Figure 5. Comparison accuracy with the literature.

V. Conclusion

This study demonstrates how machine learning and deep learning techniques can be applied to identify apple diseases in images or videos. The Convolutional Neural Network (CNN) and Random Forest (RF) model were employed in this research. The proposed methodology accurately recognizes apple diseases, resulting in proficient image recognition. The experimental research demonstrated that the suggested strategy performed well, with both CNN and RF classifiers outperforming other existing methodologies in the visual and parametric domains. The CNN model exhibited the highest accuracy of 99%. Future work on this project could involve a 3D exploration of apple disease detection in films and incorporating human feedback to improve the learned model and reduce false alarms.

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