Using deep learning algorithms to classify crop diseases

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ABSTRACT

The use of deep learning algorithms for the classification of crop diseases is one of the promising areas in agricultural technology. This is due to the need for rapid and accurate detection of plant diseases, which allows timely measures to be taken to treat them and prevent their spread. One of them is to increase productivity and maintain land quality through the timely detection of diseases and pests in agriculture and their elimination. Traditional classification methods in machine learning and algorithms in deep learning were compared to note the high accuracy in detecting pests and crop diseases. The advantages and disadvantages of each model considered during training were taken into account, and the Inception V3 algorithm was incorporated into the application. They can monitor the condition of crops on a daily basis with the help of new technology-applications on gadgets. Aerial photographs used by research institutes and agricultural grain centers do not show the changes that occur in agricultural grains, that is, diseases and pests. Therefore, the method proposed in this paper determines the types of diseases and pests of cereals through a mobile application and suggests ways to deal with them.

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1. INTRODUCTION

Thanks to the development of new technologies, with the help of drones in agriculture, farmers can access information about the state of the field and each specific crop. But private farmers, and small agricultural centers do not have the opportunity to purchase drones. Therefore, with the help of an accessible mobile application and for small plots owned by individual farmers, the proposed method is effective. 90,893 images were trained on a pre-trained database. Among them, for example, corn [1], wheat [2], oats [3], beans [4], peas [5], and other grains and their common diseases and pests have been considered. In this paper, the object of study is a deep learning algorithm for object and pattern recognition. The study aims to develop a cross-platform application that will determine what type and species a plant belongs to, as well as issue a certificate about it. This system provides for the main function of "determinant of plant diseases" according to a photo taken in real-time or stored in the gadget's storage. When developing an object recognition application, several important tasks had to be solved. The first task is to choose how to measure or calculate features, and the second task is related to the presentation of the resulting data. It is necessary to select the maximum possible number of features for recognizable images, taking into account the complexity and accuracy of determining the result for each feature.

Images in the database are not tied to the types of diseases and pests depending on climatic conditions. That is, many types of diseases and pests found in all possible grains have been studied. Improving objects [6]–[8] and increasing their quality in various applied tasks, in particular, in the field of agriculture, is one of the topical issues. Therefore, this paper considers a modified type of machine learning method aimed at improving reliability and reducing the number of errors. It has been observed that depending on the camera resolution of various gadgets, the image quality deteriorates when the image is enlarged. To solve this problem, machine learning methods were used to automate the scaling and enhancement of objects in images. The difference between this work from other works is the classification of the magnification result while maintaining image quality.

Nikhitha *et al.* [9] developed an easy-to-use tool that recognizes the stage of the disease and classifies it accordingly. Researchers use only Inception V3, but in this work, a combination of methods (ESRGAN+ResNet52V2)+Inception V3 is used for classification to improve the accuracy of plant disease detection. MNet: An interconnected network [10] created and published a database consisting of 12,000 color images of India's top fruits, labeled as “good” and “poor” quality. By testing Inception V3 as the proposed framework on the most popular deep learning model, conflicts and results for Inception V3, FC_Inception V3, and MFC_Inception V3 would be obtained. Experimental results show that the MFC_Inception V3 model achieved 99.92% accuracy. Based on the results achieved by these researchers, this work used the Inception V3 algorithm in combination with ESRGAN+ResNet52V2 to determine the classification accuracy of plant diseases. Ukwuoma *et al.* [11] use functional descriptions to implement the model and the problem of using deep learning to detect and classify fruits. The authors also implemented a deep learning model for fruit classification from scratch using the popular Fruits 360 dataset to help novice agronomists understand the role of deep learning in agriculture.

2. METHOD

Super high-resolution single image (SISR) is a computer vision task that reconstructs a high-resolution (HR) image from a low-resolution (LR) image. Given that images taken from various sources such as gadget cameras, computers, and satellite images are not always high resolution. Therefore, improving the quality of images used to solve important problems, for example, identifying a plant disease, requires the use of new technologies. In this work, to detect plant diseases according to the architecture, which is shown in Figure 1, the enhanced super resolution generative adversarial network module (hereinafter ESRGAN [12]–[14]) based on the generative adversarial network (GAN) structure [15]–[17] Figure 1 was added.

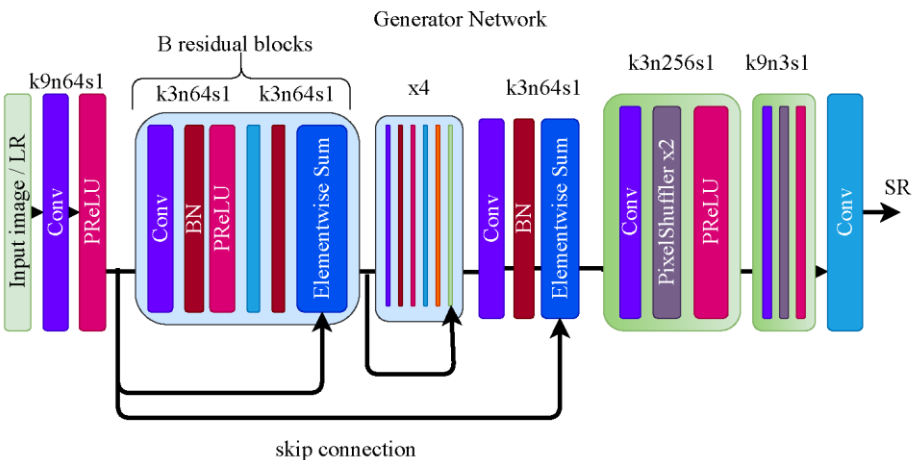

Figure 1. Enhanced super resolution GAN module architecture

As method of convolutional neural networks (CNNs), the ResNet152V2 method was used, which makes it possible to improve images. As a result of the experiment, the quality of the image obtained by the ResNet152V2 method [18], [19] is significantly improved. Solving the problem of improving image quality using neural networks, the choice was made in favor of CNNs, as they are better than others at coping with image enhancement tasks. Structured numerical data helps to train the model for further use, while deep learning does not require human intervention, when training data that has been divided for training, methods detect features on their own using layers and filters. The initial version 3 consists of symmetric and asymmetric building blocks, including convolutions, mean pooling, peak pooling, concatenation, elimination, and fully connected layers Figure 2. Batch normalization is widely used throughout the model and applied to activation inputs.

With the help of modern technologies, problems that one has to face daily are solved. One of them is monitoring the condition of crop plants [20]. In this work, it is recommended to identify and prevent diseases during their growth to obtain a good harvest of fruits. To solve the tasks, machine learning methods were considered to improve the image and the Inception V3 [21]–[23] deep learning algorithm for classification by plant diseases [24]–[26].

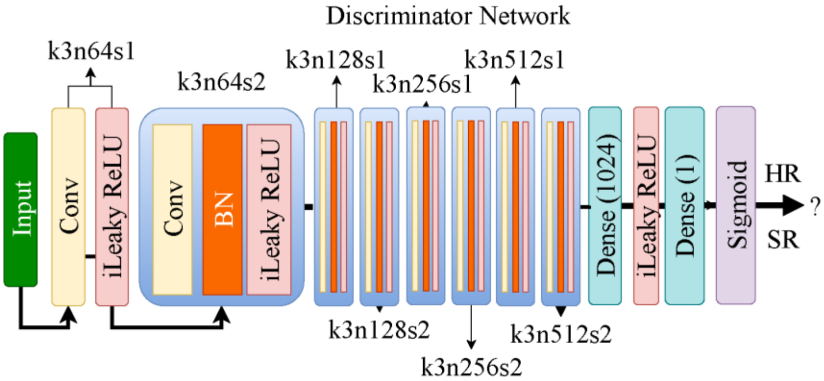

Figure 2. Inception V3 convolutional neural network architecture

3. RESULT AND DISCUSSION

3.1. Data analysis for plant disease classification

Depending on the climatic conditions of each country, the types of diseases and pests found on crops may be different. Therefore, this work involves more than one region, the preliminary database includes currently known crops and types of their diseases. The training dataset contains 30,542 pre-trained image sets taken from the Kaggle open access database. Figure 3 shows healthy and diseased varieties of the most common crops, i.e., the affected leaf of wheat as shown in Figure 3(a), the affected leaf of rice as shown in Figure 3(b), the affected leaf of corn as shown in Figure 3(c), the healthy leaf of wheat as shown in Figure 3(d). Including wheat-5215, potatoes-4793, rice-3719, corn-3534, oats-3518, peas-1946, beans-1983, flax-3200, soybeans-1785, sugar beet-799.

In this work, machine learning was performed on images of crops and their types of diseases by architecture, which is shown in Figure 1. During the experiment, the accuracy of the result when learning without improving the quality of images in the database was, on average, quite low, i.e., 85%. To improve image quality, in addition to the GAN model, the ResNet52V2 algorithm was trained, and the accuracy of the result obtained by retraining using the Inception V3 classification algorithm averaged 98% Table 1.

3.2. Implementing a mobile application with deep learning algorithms

To start the application, you need to select the type of image upload. Users can upload an image through the gallery or take a picture through the smartphone's cameras. Thus, an input image is introduced, which passes through the first trained GAN-based model, with the ESRGAN method, which performs the function of improving image quality as shown in Figure 4. After obtaining a high-quality image, the drawing is passed through a second trained CNN-based model with the Inception V3 method, which in turn performs classification to detect crop diseases such as wheat, rice and corn. After passing the models, a percentage prediction is eventually provided for any plant disease.

Based on the experiment, 30542 sets of images were examined. To see the likelihood of disease development, the model was fitted with and without the ResNet152v2 method improvement. The original image has been pre-processed according to sample requirements. Figure 5 shows the learning curves for the Inception V3 algorithm, i.e., the accuracy plot in Figure 5(a) and the data loss plot for testing in Figure 5(b) assumed in this article.

Inception V3 was initially trained on a pre-trained dataset that contains 30542 images. The accuracy of deep learning when training with the Inception V3 method was 94%, and when testing it was 92%. According to this model, the losses during training were about 6%, and during testing -8%.

In Figure 6 shows the interface of the developed mobile application, that is, the definition of diseases of crops, namely the definition of diseases of wheat is shown in Figure 6(a) and rice is shown in Figure 6(b). Figure 6 shows the interface of the developed mobile application. The interface of the created mobile application is simple and clear to the user. The mobile application is designed for farmers. The user can upload and save any image and determine the crop and its status in real-time through the application.

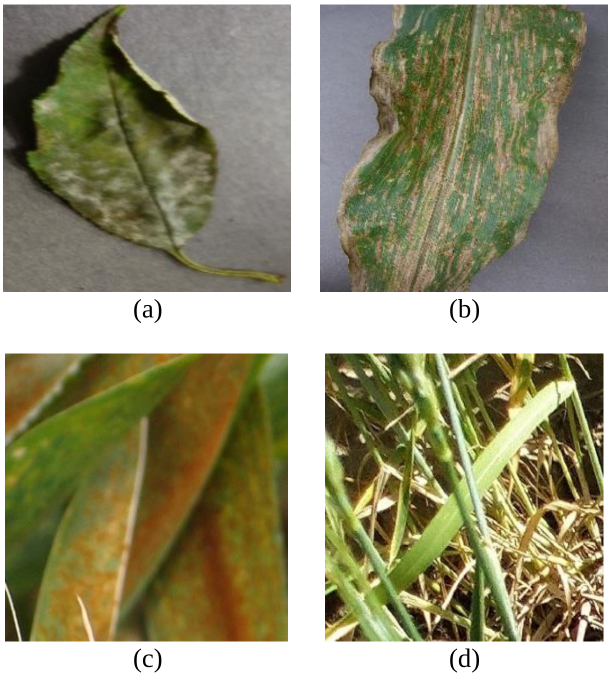

Figure 3. Original images of plant leaves (a) affected leaf of wheat, (b) affected leaf of rice, (c) affected leaf of corn, and (d) healthy leaf of wheat

Table 1. The average accuracy of determining diseases of indoor and garden plants

Source images	Inception V3	(ESRGAN+ResNet52V2)+Inception V3
Potatoes	85%	93%
Rice	87%	95%
Corn	84%	90%
Oats	86%	95%
Peas	87%	93%
Beans	84%	90%
Linen	87%	95%
Soy	86%	93%
Sugar Beet	89%	95%

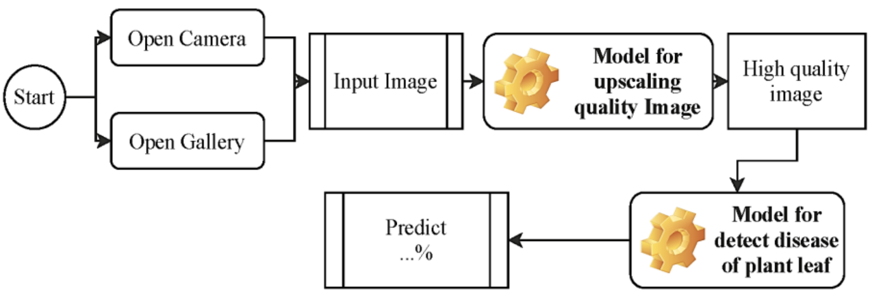

Figure 4. The architecture of the mobile application for plant disease detection

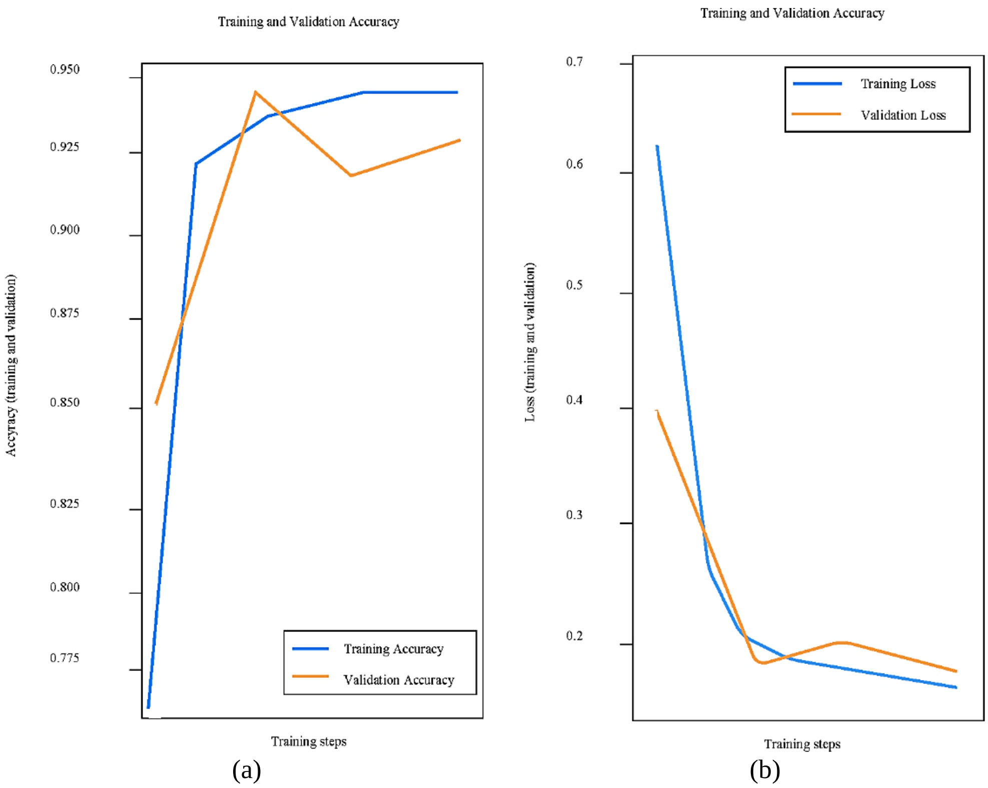

Figure 5. The result of learning Inception V3 (a) accuracy plot and (b) loss plot

Figure 6. Definition of disease of crops (a) definition of diseases in wheat and (b) in rice

4. CONCLUSION

The data was pre-trained and trained with super-resolution advanced generative adversarial network models and combined with the ResNet152V2 CNN. A study with combined use of a CNN showed high accuracy rates. That is, the joint use of the ESRGAN algorithm with a CNN showed an average of

ESRGAN+ResNet152V2+Inception V3 94% accuracy than Inception V3 86%. In this work, 30,542 pre-trained datasets of many common crop species and their diseases are included. As image classification methods, the performance of a deep learning method such as Inception V3 has been analyzed. Many scientific studies use the ESRGAN model to improve the image. In our work, a CNN was added to the existing ESRGAN model, and a better result was achieved than the Inception V3 deep learning method itself. Using a mobile application, the user can determine the type of crops and the presence of diseases in them from photographs stored in the gallery, or using a camera in real-time. In the future, taking into account the climatic conditions of the region, changes in the environment, and scientific innovations in the field of agriculture, we will include new types of crops and their diseases in the database.

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