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Analysis of Rice Leaf Diseases with Deep Learning

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Abstract – In middle-income countries, access to food is gaining importance. The inability to obtain the desired harvest from rice products, which are widely produced in countries where access to food is difficult, affects the farmer, the consumer and the country's economy. In order to reduce this impact, technology-based solutions should be integrated into agricultural production. Rice, which feeds a large part of the world's population, especially in Asian countries, can be grown throughout the world. However, rice production has been struggling with many difficulties for centuries due to various reasons such as bacterial, viral and virus. Diseases in rice product can occur in very different structures such as stem, root, leaf and stem. In this study, a new 13-layer Convolution Neural Network (CNN) model is proposed to classify the diseases in rice leaves. In order to compare the effectiveness of the proposed model, a comparison was made using a basic model consisting of two different transfer learning-based architectures named Inception and ResNet. As a result of the analyzes made, the transfer learning-based InceptionResNetV2 model gave more successful results than the proposed CNN model during the training phase. However, when the validation results were examined, the performance results of the proposed CNN model and the InceptionResNetV2 model were similar. In fact, the proposed CNN model gave slightly less losses and provided a better result than a model with a high amount of parameters such as InceptionResNetV2.

Keywords –Rice, Leaf Disease, Transfer Learning, Deep Learning, CNN, InceptionResNetV2

I. INTRODUCTION

Plant diseases inhibit the growth and development of plants. At the same time, it causes a decrease in production in terms of quantity and quality by interrupting agricultural production. The decrease in production directly affects consumption, causing either the use of imported products or an increase in the price of the products. Farmers who detect and treat diseases with the naked eye with traditional methods are not able to notice the diseases. In this case, the disease progresses, causing the products to be infected with advanced disease. Due to the reasons and reasons stated, it is important to automatically examine and analyze the diseases of plants.

The use of technology is important for the diagnosis of plant diseases that have turned into epidemics due to various reasons such as weather anomalies [1]. Thanks to the technology used, it is possible to control the diseases that have become epidemic and prevent the disease from spreading and causing greater damage. Today, many countries rely on agricultural production. Considering that most of the country's population lives on agricultural production, it is a great loss that the expected production cannot be realized due to various reasons. Diseases caused by bacteria, viruses, parasitic, fungal, viral or fungi are the factors in the formation of these losses [2]. Diseased leaves due to bacterial causes have soft spots, wilt and blight. It is generally stated that it is viral-based in those with mottling, deterioration and breakage. It can be said that fungal diseases occur in the case of rust, spots, sooty molds or rot [2]. Diseases caused by the specified sources leave a damage on the plant. Although the symptoms resulting from these damages give information about the disease, it is difficult to distinguish with the naked eye with high precision. At the same time, it needs a very long time and capital as it needs to be carried out with expert workforce. Illusions, which may occur when potential experts work for a long time, adversely affect classification.

Deep learning can provide training in many areas from root segmentation to fruit counting, from weed and seed detection to classification of plant diseases in precision agriculture. It can predict the output label by automatically learning the features given as input with the help of layers defined one after the other in deep learning. Although deep learning is similar to classical artificial neural networks, it allows to interfere with the parameters of the operations performed in the inner structure of the layers. Basically, it consists of input layer, convolution layer, pooling layer, batch normalization layer, dropout layer, fully connected layer and classification layers.

In this study, automatic classification of rice diseases in leaves was provided with a model based on both CNN and InceptionResNetV2 architectures. The results of both models have been controversially compared. Rice diseases are seen not only in leaves, but also in structures such as stem, stem and root. In order to analyze the diseases occurring in other building regions, it is necessary to have images from the specified disease regions. In further studies, effective analysis of diseases that can be found in different regions can be carried out for precision agriculture.

The main contributions of the study to the literature;

- A new CNN model consisting of 13 layers has been proposed in the data augmented data set.
- A model based on InceptionResNetV2 architecture consisting of 783 layers without performing any data augmentation is proposed.
- Two different models are proposed that can compete with each other without transfer learning and without transfer learning.

The rest of the study consists of related works, material and methods, results and discussion, and conclusion sections. Studies close to the work carried out within the scope of this article were reviewed in Related Works. Material and methods used and proposed methods are explained in the Material and Methods section. Performance results obtained within the scope of the study are presented in the Results and Discussion section. In the conclusion part, the study was concluded by planning future studies.

II. RELATED WORKS

In order to increase the quality and quantity of plants, it is necessary to reduce plant diseases [3]. At this point, it seems that many researchers use computer vision techniques to identify unusual growth and dysfunction in plants [4], [5].

Shrivastava et al. CNN tabanlı bir transfer öğrenme tekniği ile 4 farklı pirinç hastalığını sınıflandırmak için gerçekleştirmiştir [6]. Vanitka performed the classification of four different rice diseases with VGG16, ResNet50 and Inception V3 transfer learning techniques [7]. Upadhyay and Kumar classified four different rice diseases with a high performance with the fully connected CNN structure [8]. Yao et al. developed three different rice disease classification methods with the SVM-based classification method [9]. While RGB color channels were reduced to 2 channels, segmentation was performed with the Otsu method. It is seen that textural features used in classical machine learning structures are used. Atabay et al. developed two different CNN architectures with VGG16 and VGG19 architectures for the classification of tomato diseases. Residual learning is used in the CNN model they developed. They state that the residual connected CNN model has more successful results than other models. Liang et al. extracted features by CNN methods based on wavelet transform, local binary patterns histograms for rice blast recognition [10]. Extracted features present classification performance results obtained from classical feature extraction data and CNN-based feature extraction data with SVM classifier.

III. MATERIALS AND METHOD

A. *Materials*

The rice leaf dataset used in the article contains data on three different types of leaf diseases [11]. Each disease class contains 40 images. Total number of images is 120. Images of the three most common rice leaf diseases, namely leaf smut, bacterial leaf blight and brown spot, are included in the dataset. There are inadequacies in the number of data compared to the studies in the literature [10]. In further studies, it would be more appropriate to expand the data set.

In both models proposed in this study, Adamax [12] uses the activation function. The training process was carried out with 50 epochs worth of iterations. Tensorflow and keras libraries were used to create the models.

B. *Proposed CNN*

There are 13 layers in total in the proposed system for the classification of rice diseases. In the first layer, the input layer, the image is enhanced with Random Flip. Image input dimensions are 180x180. In the second layer, 16 filters with cellular activation function of 5x5 filter sizes were used. In the third layer, a layer is defined in which 2x2 filter sizes are selected with a maximum of 2 strides. In the fourth layer, the convolution layer is defined with 32 filters and 5x5 windows. In the fifth layer, a new pooling layer is defined with the parameters specific to the maximum pooling layer in the third layer.

In the sixth layer, the distinctive features were extracted with the convolution layer defined with 64 filters in 5x5 dimensions. In the structure in the third and fifth layers, a maximum pooling is defined in the seventh layer. In the eighth layer, 128 filters were applied as a convolution layer with 5x5 windows. In the ninth layer, a maximum pooling layer with 2x2 strides value of 2 is defined. In the tenth layer, the dropout layer, which leaves 0.8 neurons, is defined. In the eleventh layer, the Flatten layer is defined, which transforms the extracted feature vector. In the twelfth layer, a fully connected layer with 128 neurons with ReLU activation function is defined. In the thirteenth layer, the classification layer is defined.

C. *InceptionResNetV2*

InceptionResNetV2 is a combination of residual blocks [13] and versions of the Inception architecture [14]. Inception architectures are composed of many branched structures. Split transform merge architecture has a strong representation ability in the architecture formed by combining filters of different sizes [15]. The architecture includes Inception ResNet A, Inception ResNet B and Inception ResNet C blocks [15]. The proposed InceptionResNetV2 model consists of input, Stem, 5x Inception ResNet A, Reduction A, 10x Inception ResNet B, Reduction B, 5x Inception ResNet C, Dropout, average pooling, Dropout, Flatten, fully connected layer and softmax activation functions. Its top layer is modified according to the data set given as input. Added a dropout, a Flatten layer to the basic InceptionResNetV2 model, which performs a 0.9 percent neuron drop.

IV. RESULTS AND DISCUSSION

In this article, the performance results of two different models proposed for the classification of foliage diseases of rice plants are presented in this section.

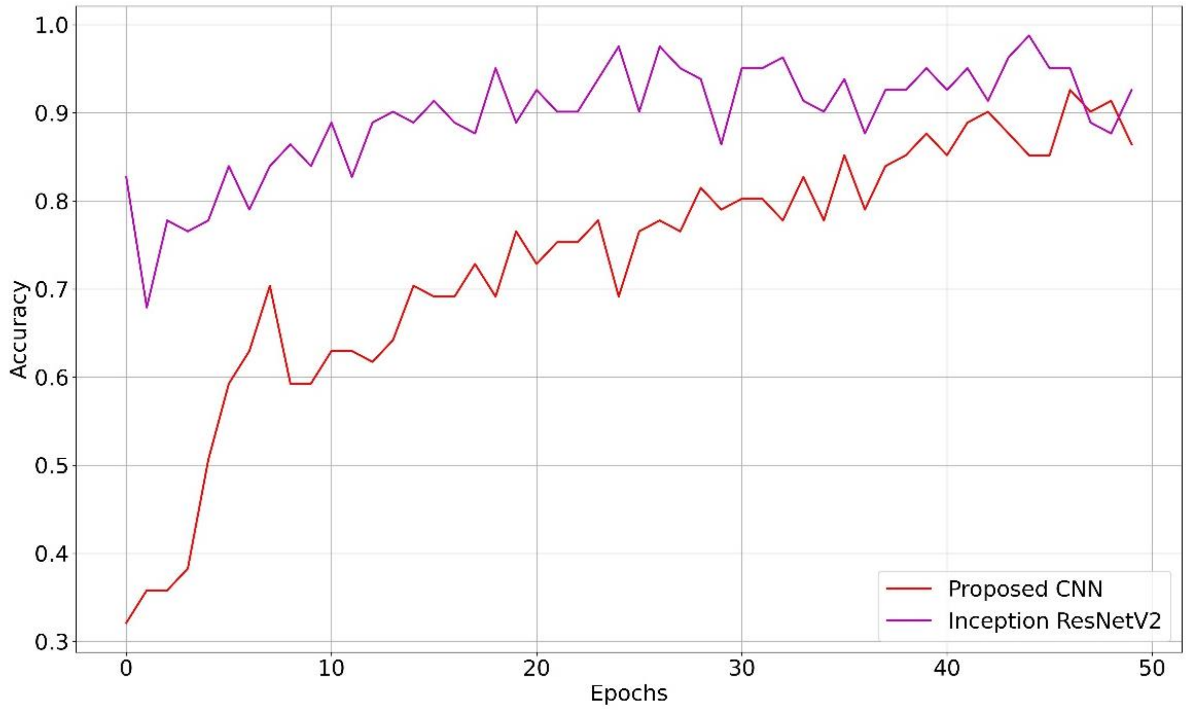

Fig. 1. Train accuracy

The proposed CNN model achieved a training accuracy of 0.86. InceptionResNet V2 model achieved 0.92 train accuracy performance result.

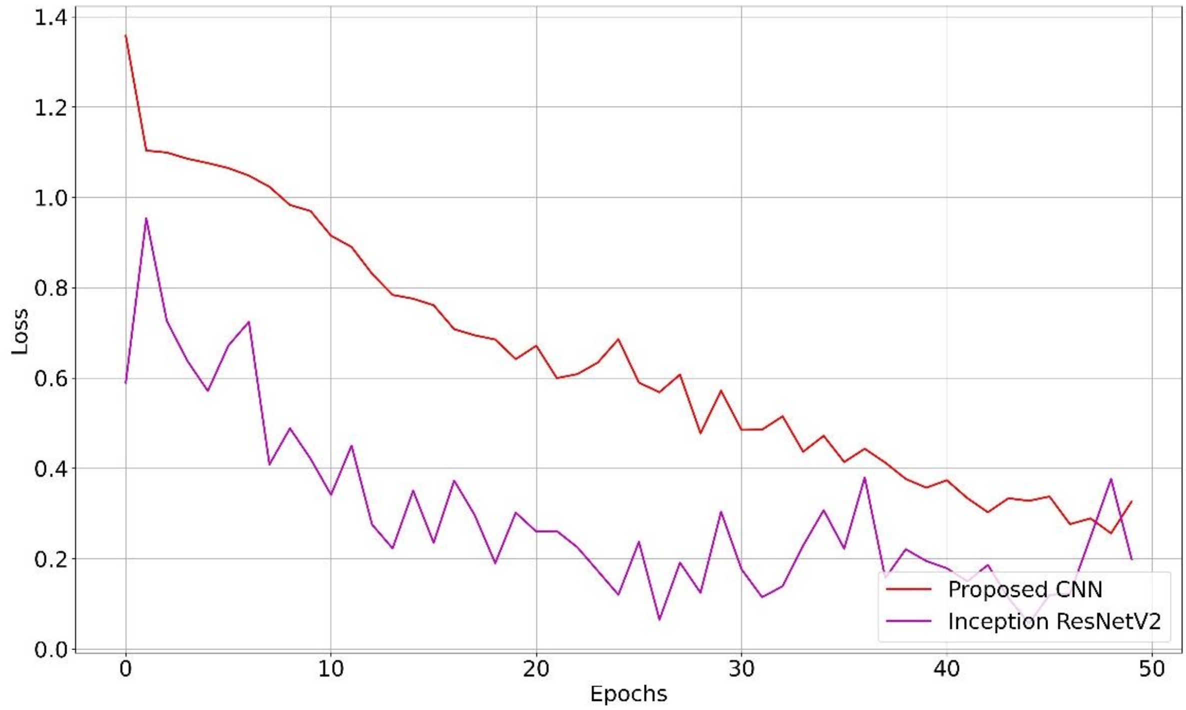

Fig. 2. Train loss

The InceptionResNetV2 model has reached a train loss of 0.19. The Proposed CNN model, on the other hand, reached a train loss value of 0.32.

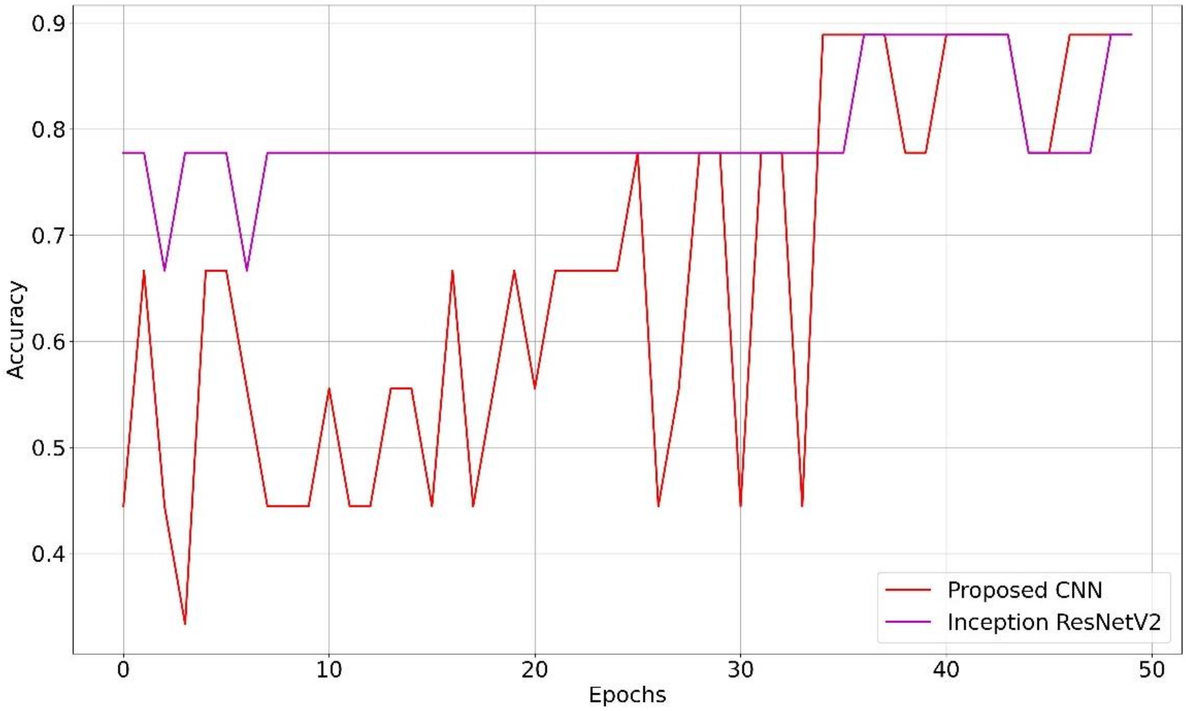

Fig. 3. Validation accuracy

The proposed CNN model achieved a validation accuracy performance result of 0.88. At the same time, it reached a validation loss performance result of 0.37. While the InceptionResNetV2 model reached 0.88 validation accuracy performance results, it reached 0.43 validation loss.

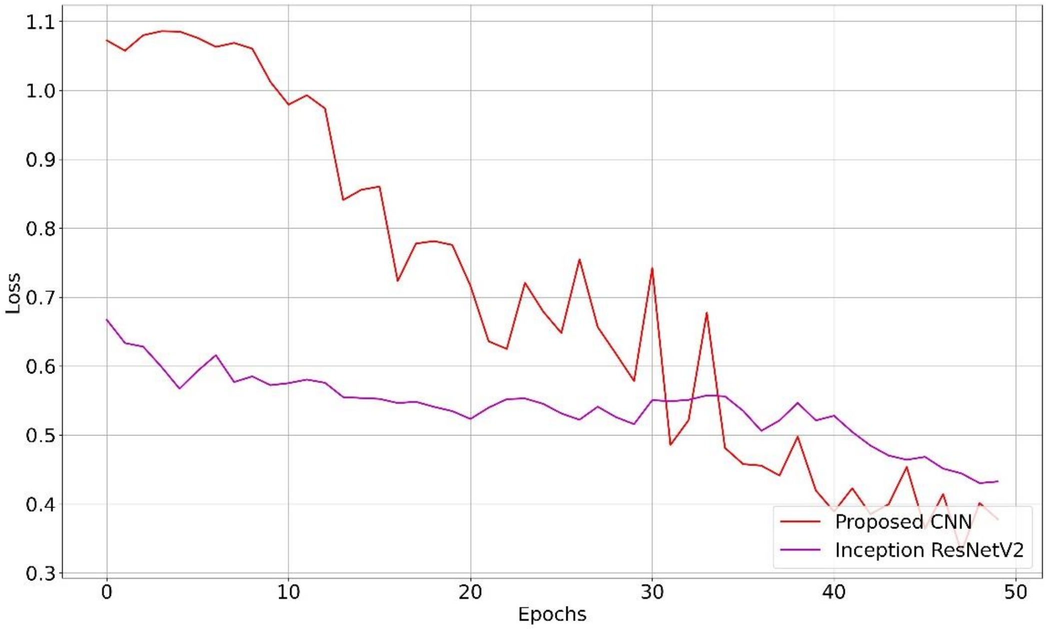

Fig. 4. Validation loss

When the performance results in Figures 1-4 are evaluated together, the train performance results are obtained from the InceptionResNetV2 model. However, the proposed CNN model can compete with InceptionResNet V2 in terms of performance, validation accuracy and loss rate. In fact, the proposed CNN gave less loss than the InceptionResNetV2 model.

V. CONCLUSION

Diseases in different locations of the plant affect the continuity of production. Since this problem is quite large, a new model has been proposed to classify diseases that occur only on leaves. The proposed CNN model is compared with another model based on the transfer learning-based InceptionResNetV2 architecture. A study that can compete with both models has been put forward. In both models, 88% success rate was achieved by running 50 epochs. The proposed CNN model gave a slightly better result than the InceptionResNetV2 model. In future studies, it is possible to classify not only rice diseases that occur on leaves, but also diseases that occur in structures such as stems and stems, with a single deep learning model. In addition, a faster result can be achieved in finding the best by using optimization methods in the determination of hyperparameters.

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