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A Comparative Analysis of Deep Learning Parameters for Enhanced Detection of Yellow Rust in Wheat

Buğdayda Sarı Pasın Gelişmiş Tespiti için Derin Öğrenme Parametrelerinin Karşılaştırmalı Analizi

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Abstract

Wheat, one of the most important food sources in human history, is one of the most important cereal crops produced and consumed in our country. However, if diseases such as yellowpas, which is one of the risk factors in wheat production, cannot be detected in a timely and accurate manner, situations such as decreased production may be encountered. For this reason, it is more advantageous to use decision support systems based on deep learning in the detection and classification of diseases in agricultural products instead of experts who perform the processes in a longer time and have a higher error rate. In this study, the effects of the number of layers, activation function and optimization algorithm variables on the classification of deep learning models used for the classification of yellow rust disease in wheat were examined. The 90.87% classification success obtained with the default parameters at the beginning of the study was increased to 97.36% by optimizing the convolutional neural network parameters at the end of the study. As a result of the study, the highest success value was obtained when using a 5-layer CNN model using the Leaky ReLU activation function and the Nadam optimization algorithm.

Key Words

"Wheat, Yellow Rust, Deep learning, Activation function, Optimizer"

Öz

İnsanlık tarihinin en önemli besin kaynaklarından biri olan buğday ülkemizde de üretimi ve tüketimi yapılmakta olan en önemi tahıl ürünlerinden biridir. Fakat buğday üretimindeki risk faktörlerinden biri olan sarıpas gibi hastalıkların zamanında ve doğru bir şekilde tespit edilememesi durumunda üretimin azalması gibi durumlarla karşı karşıya kalınabilmektedir. Bu nedenle zirai ürünlerdeki hastalıkların tespit ve sınıflandırılması işlemlerinde daha uzun sürede işlemleri gerçekleştiren ve hata yapma oranı daha yüksek olan uzmanlar yerine derin öğrenmeye dayalı karar destek sistemlerinin kullanılması daha avantajlıdır. Bu çalışmada da buğdaydaki sarı pas hastalığının sınıflandırılması işlemleri için kullanılan derin öğrenme modellerinde katman sayısı, aktivasyon fonksiyonu ve optimizasyon algoritması değişkenlerinin sınıflandırmaya etkisi incelenmiştir. Çalışma başlangıcında varsayılan parametrelerle elde edilen %90,87 sınıflandırma başarısı, çalışma sonunda evrişimsel sinir ağı parametrelerinin optimize edilmesiyle %97,36 seviyesine yükseltilmiştir. Çalışma sonucunda en yüksek başarı değeri Leaky ReLU aktivasyon fonksiyonu ve Nadam optimizasyon algoritması kullanan 5 katmanlı CNN modeli kullanıldığında elde edilmiştir.

Anahtar Kelimeler

"Buğday, Sarı Pas, Derin Öğrenme, Aktivasyon Fonksiyonu, Optimizasyon"

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1. Introduction

Wheat (Triticum sp.) is one of the most important food sources throughout human history and is a cereal crop that is widely produced and consumed both in the world and in our country. Due to the fact that wheat has an extremely high adaptability, its cultivation, maintenance, harvesting, storage, transportation and even marketing are relatively easier than other crops, and that it meets a significant portion of the daily calories of human beings, it ranks among the most cultivated and produced agricultural products in the world from past to present (Tadesse vd., 2019). According to Statista data, 779.33 million tons of wheat were produced in the world during the 2021-2022 production season (Statista, t.y.). Wheat production is carried out in almost all regions of our country and in 2022, 19,750,000 tons of wheat was produced in 6,6287,386 da-1 area in our country. (TUIK, t.y.). Abiotic factors such as climatic conditions, geographical conditions, faulty agricultural practices and biotic factors such as pests, weeds and diseases that affect wheat production in our country and in the world are among the important factors that affect yield and quality parameters during the wheat production season and limit production. One of the most important biotic factors limiting wheat production and quality worldwide and in our country is yellow rust (Puccinia striiformis f.sp tritici) disease. Yellow rust disease is seen as the most important biotic factor limiting wheat production in the last 15-20 years and it has been determined as a result of studies that 88% of the world wheat production areas are affected by this disease (Beddow vd., 2015; Schwessinger, 2017). It is estimated that 5 million tons of product is lost annually in wheat production areas infected with yellow rust disease and the value of the lost product is approximately 1 billion USD (Schwessinger, 2017). Yellow rust develops at lower temperatures (10- 15°C) than other rust diseases and is the most effective type of rust (Chen, 2005). The summer spores of yellow rust are formed earlier than the pycnidial stage of Septoria. The summer spores (urediospores) of yellow rust are replaced by winter spores (teliospores) at the end of the season. In wheat, the formation of winter spores of yellow rust coincides approximately with the formation of pycnids, a symptom of septoria leaf spot (AHDB, 2020). For this reason, the similar symptoms of these diseases and the coincidence of their occurrence times may cause even agricultural professionals working in the field to misdiagnose them from time to time. The detection and follow-up of yellow rust disease, one of the wheat leaf diseases, is carried out by researchers specialized in the field. Until the disease is detected and the necessary measures are taken, the crop is left at risk. Considering the human factor, the fact that the manual evaluation of the disease can be done objectively at any time and anywhere has become a controversial issue. Considering all these factors, there is an increasing need for automated decision support systems that will help experts to accurately detect yellow rust disease, one of the risk factors in wheat production, at different stages.

With the development of technology, artificial intelligence has started to be used in plant disease detection and prevention studies (Toda & Okura, 2019). Machine learning, one of the sub-branches of artificial intelligence, is a set of algorithms that enable stable predictions about unknown situations based on existing data (El Naqa & Murphy, 2015). In this context, deep learning, a special branch of machine learning, stands out with its ability to recognize more complex and high-level patterns by analyzing large amounts of data.

Studies have been conducted with deep learning techniques to address risk factors in wheat production and to improve the detection of yellow rust disease. These studies highlight the potential of using artificial intelligence and deep learning algorithms in plant disease detection. In this context, the use of advanced technologies to optimize wheat production and combat diseases has become an important research area.

1.1.Related Works

There are various studies in the literature on the detection of yellow rust disease, one of the wheat leaf diseases, with deep learning algorithms. As a result of the literature review, six different studies were analyzed. In the study conducted by Long et al., deep learning models (MobilNet InceptionV3, VGG16, Xception, Creal Conv) were tested on a dataset with 5 classes including 4 different diseases (yellow rust, brown rust, powdery mildew, septoria) and healthy. As a result of the analyzes, Creal Conv model was the winner with 97.5% success rate (Long vd., 2023). Mi et al. applied deep learning models DenseNet, C-DenseNet models by grading the severity of yellow rust disease in their study. As a result of the classification process, the C-DenseNet model achieved the highest success with an accuracy rate of 97.99 (Mi vd., 2020). Bukhari et al. classified yellow rust pathogen as healthy, susceptible and resistant on wheat leaves. They tested Watershed, Grab Cut, U2-Net, ResNet18 models and obtained the highest accuracy rate of 96%, 196% with the U2-Net model (Bukhari vd., 2021). In the study conducted by Genaev et al., EfficientNet, EfficientNet-B0_FDA algorithms from deep learning models were tested in a dataset with 5 classes including 4 different diseases (brown rust, black rust, powdery mildew, septoria) and healthy. As a result of the study, EfficientNet-B0_FDA model gave the highest success rate with 94% accuracy rate (Genaev vd., 2020). In their study, Tang et al. developed ResNet, a neural network-based image classifier to effectively monitor yellow rust (Puccinia striiformis f.sp tritici), one of the most destructive diseases of wheat. They acquired images for RGB images and videos from wheat production fields with different wheat types (winter, spring), conditions (irrigated and non-irrigated) and locations using UAVs and smartphones. They obtained the images with semi-automatic machine labeling. As a result of the study, a success rate of 86% was determined with the ResNet model (Tang vd., 2023). In their study, Feng et al. analyzed powdery mildew disease images with different monitoring techniques (thermal infrared, hyperspectral and RGB) that significantly affect the yield and growth of wheat crops. They used these techniques for prediction using different machine learning algorithms (PLSR, SVM and RFR). As a result, the RFR model had the optimum prediction performance with R^2 values of 0.872 and 0.862 for calibration and validation, respectively (Feng vd., 2022). In this study, unlike the literature, the effects of the number of layers, activation function and optimization algorithms, which are important parameters of convolutional neural networks, on classification are analyzed and evaluated separately. Thus, each parameter is evaluated in detail within itself.

1.2. Motivation and Our Model

Classifying the quality of agricultural products using computer vision methods is critical both to increase crop productivity and to manage workers' time more effectively. Furthermore, these methods allow for higher accuracy in classification. Many researches focus on processing images of agricultural products with various deep learning and machine learning techniques and classifying product quality based on the results obtained. In this study, we investigate the effect of the number of layers, activation function and optimization algorithms on the classification process with convolutional neural networks.

In the study, wheat images were obtained and then these images were categorized and a new data set was obtained by applying data augmentation processes (90º and 180º rotation). Then, 3 different layers (3,4 and 5), 7 different activation functions (ReLU, Leaky ReLU, Swish, Sigmoid, Tanh, ELU and SELU) and 7 different optimization algorithms (Adam, SGD, RMSprop, AdaDelta, AdaGrad, Adamax and Nadam) were used and the results were analyzed while performing classification processes with convolutional neural networks using this data set.

1.3. Novelties and Contributions

The innovations of our study are as follows:

- A unique dataset was created for the detection of yellow rust disease in wheat. This dataset consists of carefully selected and diversified images of wheat grown in the Agricultural R&D area of ... University of ... to form the basis of the research. This unique dataset represents the various conditions and disease stages necessary for the deep learning model to detect this disease more effectively.
- While in the studies in the literature, the effects of the parameters are applied with tunning operations, in this study, the study was carried out step by step in order to analyze the effects of 3 different parameters separately. Thus, the effect of each parameter on classification success was evaluated separately.
- In the study, the classification process with an initial success rate of 90.87% with the default values was increased to 97.36% as a result of the study.

In this study, the effects of the number of layers, activation function and optimization algorithm on deep learning methods used in the detection of wheat leaf diseases were examined and the results were evaluated. In the rest of the paper, the second section describes the data set used in the study, the preprocessing performed and the methods used in the study. In the third section, the results and discussion are presented. In the last section, the results and the planned study to be carried out after the study are mentioned.

2. Materials and Method

In this study, healthy and yellow rust disease images obtained from different wheat genotypes grown in the Agricultural R&D …………………. in the 2023-2024 production season were used.

2.1. Dataset

The data set used in the study was categorized into two main categories: healthy and yellow rust infected wheat leaves. All images were saved in JPG format at high resolution. In order for the deep learning models to produce more accurate results, the dataset was augmented with artificial data. The original number of classes in the dataset and the number of classes after the artificial data were generated are shown in Table 1.

Table 1. Dataset image counts

Category	Original Dataset	Dataset After Preprocessing
Yellow Rust	1572	1572
Healthy	377	897
Total	1949	2469

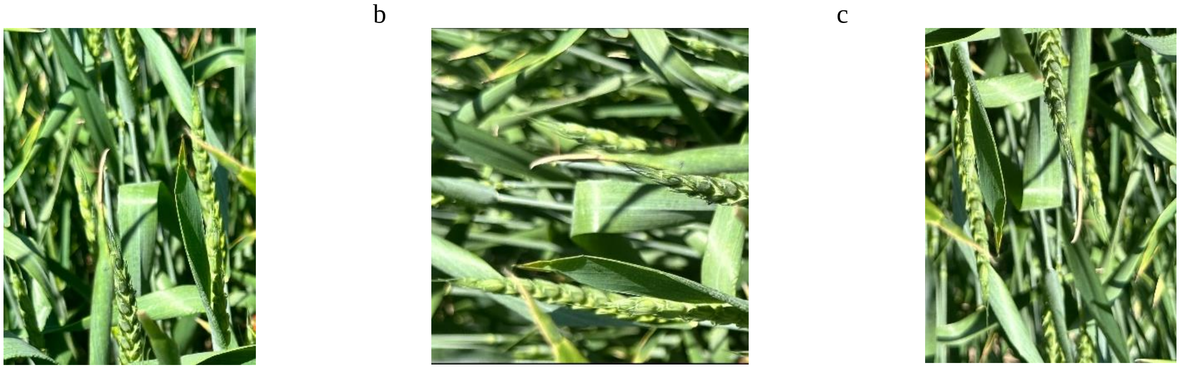
The images in the data set are shown in Figure 1.

a b

Figure 1. (a) Healthy image from the data set **(b)** Yellow rust (Urediospor/ Teliospor) images from the data set

Sample visualizations of the data set augmentation phase are shown in Figure 2.

a b c



Figıre 2. (a) Original Image (b) Image Rotated 90^o (c) Image Rotated 180^o

This data set was divided into test and training data sets to be used in deep learning techniques. At this stage, 80% of the data set obtained after preprocessing is divided into training and 20% for testing. The detailed distribution of training and test data is shown in Table 2.

Table 2. Training / Test data set distribution

Category	**Train**	**Test**
Yellow Rust	1258	314
Healthy	718	179
Total	1976	493

2.2. Convolutional Neural Networks

A convolutional neural network (CNN) is a feed-forward neural network with a deep structure for analyzing visual images. It is often used in various computer vision processes such as classification, object detection, segmentation and image rendering. (Heo vd., 2023; Yue vd., 2023; Özbay vd., 2023). The choice of the number of layers, activation functions and optimization algorithms is critical in the design of a convolutional neural network. The number of layers affects the complexity of the network and the risk of overfitting. Activation functions determine neuron outputs and play an effective role in the learning ability of the model. The choice of optimization algorithms drives the training process and should be chosen carefully depending on the type of data and problem complexity.

2.2.1. Number of layers

CNNs basically consist of an input layer, a convolution layer, a pooling layer, a fully connected layer and an output layer. The convolution layer is responsible for extracting features from the data by applying filters. The pooling layer reduces the size of the feature maps and thus reduces the computational complexity. The fully connected layer connects the extracted features to the output layer to perform classification/prediction based on the learned features. Intermediate layers such as convolutional layer and pooling layer are called hidden layers. Hidden layers enable the learning process to be performed more efficiently and thus more successful results are obtained. (Ahad vd., 2023; Yildirim & Çinar, 2021). The number of layers is a critical factor determining the complexity of a convolutional neural network. More layers can enable the network to learn deeper features, but can also lead to overfitting. Therefore, choosing an appropriate number of layers is critical to achieve balance.

2.2.2. Activation functions

Activation functions are mathematical functions used to make the outputs of neurons in neural networks non-linear. These functions take a weighted sum of the inputs and apply a non-linear transformation to produce the output of the neuron. Furthermore, these functions help to compress the inputs into the desired range and allow the network to learn complex relationships. In the absence of activation functions, neural networks can only learn linear relationships and cannot recognize more complex relationships (Ramadevi vd., 2024). In summary, choosing the appropriate architecture and activation function in deep learning studies has an important role in achieving more successful and higher performance results (Adem, 2022). In this study, 7 different activation functions were used: ReLU, Leaky ReLU, Swish, Sigmoid, Tanh, ELU and SELU.

2.2.3. Optimization algorithms

Optimization algorithms are functions used in deep learning processes that minimize the difference between the prediction produced by the network and the actual value, i.e. the error rate. These functions work to minimize the amount of error through weight update operations. Thus, it is aimed to complete the learning process more effectively and successfully. For this reason, the optimization algorithm should be selected correctly in order to minimize the error during deep learning processes (Jentzen & Welti, 2023; Seyyarer vd., t.y.). In this study, 7 different optimization algorithms were used: Adam, SGD, RMSprop, AdaDelta, AdaGrad, Adamax and Nadam.

3. Results and Discussion

First, data augmentation operations were performed to solve the imbalance in the number of data belonging to the healthy and yellowpas classes. Within the scope of data augmentation, new images were obtained by rotating the existing images of the healthy data class by 90° and 180°. After the operations, there are 2469 images in the dataset, including 1572 yellowpas and 897 healthy images.
The diagram of the model used in the study is presented in Figure 3.

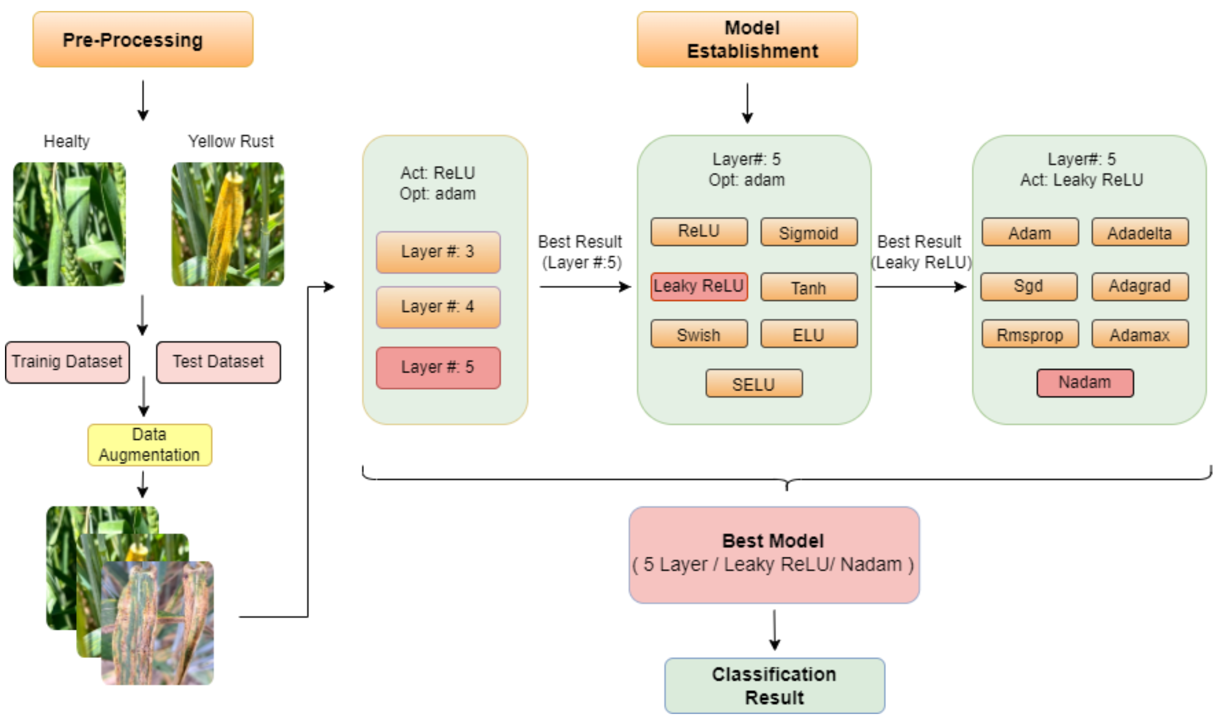


Figure 3. Model Used in the Study

After preprocessing, the results obtained by keeping the Activation Function (ReLU) and Optimization Algorithm (Adam) values constant and changing the number of layers were evaluated in order to observe the effect of the number of layers in deep learning processes. In the study, studies were carried out for 3, 4 and 5 layers. The details of the models run with different number of layers are shown in Figure 4.

3-Layer CNN Model

Layer	Output Shape	Param #
Rescaling	(None, 180, 180, 3)	0
Conv2D	(None, 180, 180, 16)	448
MaxPooling2D	(None, 90, 90, 16)	0
Conv2D	(None, 90, 90, 32)	4640
MaxPooling2D	(None, 45, 45, 32)	0
Conv2D	(None, 45, 45, 64)	18496
MaxPooling2D	(None, 22, 22, 64)	0
Flatten	(None, 30976)	0
Dense	(None, 128)	3965056
Dense	(None, 2)	258

4-Layer CNN Model

Layer	Output Shape	Param #
Rescaling	(None, 180, 180, 3)	0
Conv2D	(None, 180, 180, 16)	448
MaxPooling2D	(None, 90, 90, 16)	0
Conv2D	(None, 90, 90, 32)	4640
MaxPooling2D	(None, 45, 45, 32)	0
Conv2D	(None, 45, 45, 32)	9248
MaxPooling2D	(None, 22, 22, 32)	0
Conv2D	(None, 22, 22, 64)	18496
MaxPooling2D	(None, 11, 11, 64)	0
Flatten	(None, 7744)	0
Dense	(None, 128)	991360
Dense	(None, 2)	258

5-Layer CNN Model

Layer	Output Shape	Param #
Rescaling	(None, 180, 180, 3)	0
Conv2D	(None, 180, 180, 16)	448
MaxPooling2D	(None, 90, 90, 16)	0
Conv2D	(None, 90, 90, 16)	2320
MaxPooling2D	(None, 45, 45, 16)	0
Conv2D	(None, 45, 45, 32)	4640
MaxPooling2D	(None, 22, 22, 32)	0
Conv2D	(None, 22, 22, 32)	9248
MaxPooling2D	(None, 11, 11, 32)	0
Conv2D	(None, 11, 11, 64)	18496
MaxPooling2D	(None, 5, 5, 64)	0
Flatten	(None, 1600)	0
Dense	(None, 128)	204928
Dense	(None, 2)	258

Figure 4. CNN models with different number of layers

When the Activation Function ReLU is kept constant as the Optimization Algorithm adam, the results obtained when the classification processes are performed for layers 3, 4 and 5 are shared in Table 3. According to these results, it is seen that the highest success (94.73%) is obtained in the model with 5 layers. The results of the study show that the success increases as the number of layers increases. When the number of layers is increased further, it is seen that the results remain stable and the success is not increased. This shows the importance of selecting the appropriate number of layers to ensure balance.

Table 3. Results obtained from the model with different number of layers

Layer #	Activation Function	Optimization Algorithm	Accuracy
3			90,87
4	ReLU	Adam	93,71
5			**94,73**

In the second stage of deep learning studies, the effect of activation functions on deep learning methods is examined. For this purpose, in this part of the study, the number of layers, which was the number of layers with the highest success in the previous stage, was kept constant at 5 and the 'Adam' function was kept constant as the Optimization Algorithm. After these processes, the results obtained depending on the activation function variable are shared in Table 4.

Table 4. Results obtained from the model with different activation functions

Layer #	Activation Function	Optimization Algorithm	Accuracy
	ReLU		94,73
	Leaky ReLU		**96,96**
	Swish		94,12
5	Sigmoid	Adam	66,13
	Tanh		**94,93**
	ELU		93,71
	SELU		**95,33**

Considering the results, it is seen that the Tanh (94.94%), SELU (95.33%) and Leaky ReLU (96.96%) activation functions achieved higher success than the value obtained with the ReLU activation function in the previous stage. The Leaky ReLU activation function focuses on reducing the Vanishing Gradient problem, having a wider activation range and speeding up the training process (Liu vd., 2019). These features help deep learning networks to learn more effectively and generalize better, which is supported by the results shared in the Table 4.

On the third stage of deep learning studies, the effect of optimization algorithms on deep learning methods is examined. In this stage, the Leaky ReLU activation function, which achieved the highest success (96.96%) in the previous stage, and the 5-layer values are kept constant and the process is repeated for different optimization algorithms. The results obtained depending on the optimization algorithm are presented in Table 5.

Table 5. Results obtained from the model with different optimization algorithms

Layer #	Activation Function	Optimization Algorithm	Accuracy
5	Leaky ReLU	Adam	96,96
		Sgd	89,86
		Rmsprop	95,94
		Adadelta	96,75
		Adagrad	96,55
		Adamax	96,55
		Nadam	**97,36**

As a result of this stage, it was seen that the best result was obtained with a success rate of 97.36% when the Nadam optimization algorithm was used. In addition, the results of the optimizer functions and the results of the number of layers, which is our first experimental study, were plotted in a box-plot graph and stability analysis of the accuracy values were also performed and showed in Figure 5.

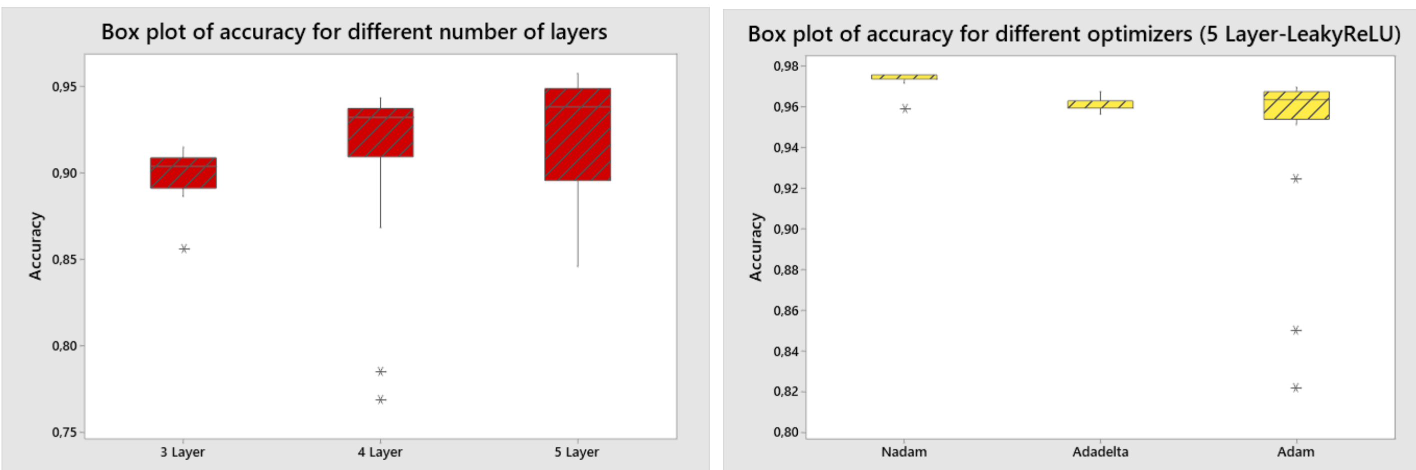


Figure 5. Box-Plot Graph of the Accuracy Values of Different Experimental Studies

Figure 5 shows the average accuracy values and standard deviations for different number of layers and different optimizer functions for deep learning models. The box plots show that the distance between the extreme values of the Nadam optimizer results is much smaller than the others. This shows that the proposed model is relatively consistent with minimal differences between the best and worst results. The box plot length and whisker length obtained from the Nadam optimizer results are shorter than the other box plots. A shorter box plot indicates that the results have less variability and are more concentrated around the median value. The Nadam activation function contributes to the fast convergence of the network by providing fast training. It also combines the advantages of momentum and decay, thus providing a balanced training process. In addition, Nadam reduces overfitting and helps the model to generalize better. (Li vd., 2020). Thanks to these features, higher success in agricultural imagery with Nadam is supported by experimental studies. As a result of all these stages, it is seen that the convolutional neural network model with 5 layers, Leaky ReLU as the activation function and Nadam as the optimization algorithm has the highest success rate of 97.36%.

4. Conclusion

Wheat is an important food source worldwide, both in production and consumption. Yellow rust disease is one of the most important factors negatively affecting wheat production, leading to major crop losses. Accurately detecting the disease in agricultural crops is a challenging task for agricultural experts, and the work can be easily affected by external factors such as fatigue, experience and lack of sleep. For this reason, different deep learning methods are used to detect diseases in agricultural products. In this study, the effects of 3 different factors such as the number of layers, activation function and optimization algorithm on the classification of agricultural images are examined. In the first stage of the study, the effect of the number of layers on the classification success was examined and it was seen that the success value increased as the number of layers increased and the highest result was obtained with the 5-layer model (94.73%), which was the highest layer in the study. However, increasing the number of layers more than necessary may cause overfitting. Therefore, choosing the appropriate number of layers is of great importance. In the second stage of the study, seven different activation functions were tested in order to examine the effect of activation functions on classification success, and the success value was increased with Tanh, SELU and Leaky ReLU activation functions, and it was seen that the highest success was obtained when using the Leaky ReLU activation function (96.96%). In the last stage of the study, seven different optimization algorithms were used to examine the effect of optimization algorithms on classification success and it was seen that the highest success was achieved with the Nadam optimization algorithm (97.36%). As a result of this study using agricultural images, the best classification process was calculated with an accuracy of 97.36% and this success was achieved with the 5-layer CNN model created using the Leaky ReLU activation function and the Nadam optimization algorithm. In future studies, the model is planned to be developed and used on decision support systems.

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