Classification of Rice Varieties Using a Deep Neural Network Model

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ABSTRACT

Deep learning is a machine learning approach that has been widely used in many different fields in recent years. It is used in agriculture for various purposes, from product classification to diagnosis of agricultural diseases. In this study, we propose a deep learning model for the classification of rice species. Rice is an agricultural product that is widely consumed in Turkey as well as in the world. In our study, a rice data set that contains 7 morphological features obtained by using 3810 rice grains belonging to two species is used. Our model consists of three hidden layers and two dropouts (3H2D) added to these layers to prevent overfitting in classification. The success of the model is compared with Logistic Regression (LR), Multilayer Perceptron (MLP), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Ada Boost (AB), Bagging (BG),and Voting (VT) classifiers. The success of these methods is 93.02%, 92.86%, 92.83%, 92.49%, 92.39% ,91.71%, 88.58%, 92.34%, 91.68%, and 90.52% respectively. The success of the proposed method is 94.09%. According to the results obtained, the proposed method is more successful than all of these machine learning methods.

1 INTRODUCTION

Deep-learning is a machine learning technique with sub-branches such as deep neural networks, convolutional neural networks, deep belief networks, and recurrent neural networks. In this study, a deep neural network is used. Deep neural networks refer to a type of learning model in which multiple layers of nodes are used to derive high level functions from the model input information. The more layers it needs to process to achieve the result, the greater the depth of the network. The use of methods based on deep learning has increased in the field of agriculture, as in many other fields, in recent years. In one study [1], deep learning-based methods are applied for weed detection in agricultural crops consisting of carrots, sunflowers, sugar beets, soybeans, and maize. In the study [2], which presents a model constructed using computer vision and a deep convolutional neural network to aid in the prediction of crop diseases, 14 crop types and 26 diseases can be identified using a dataset of both diseased and healthy plant leaves. Another study [3] presents a deep learning-based model for early prediction of crop frost to help farmers save crops. In the study [4] on products consisting of different fruits and vegetables, it is observed that the application of deep learning methods provides better accuracy for precision agriculture.

In this study, a deep learning-based classification model is proposed for two rice types patented in Turkey. Rice is an important food source for the majority of the world's population and has a large share in the global agricultural industry [5]. Rice has big significance in human nutrition in Turkey as well as in the world in terms of being economical and nutritious. In recent years, there have been many studies on rice using a deep learning approach. In the study [6], a pixel-level classification model is presented that uses convolutional neural networks to detect rice in complex landscape areas, where rice is easily mixed with its surroundings. In the study [7] to improve the accuracy of rice counting and detection in the field, is developed a panicle counting and detection system based on advanced region-based convolutional neural networks. For collecting images, unmanned aerial vehicle that has a high-definition RGB camera is used. In the study [8], an end-to-end prediction method for rice yield estimation is proposed, combining two backpropagation neural networks with an independently recurrent neural network. The study [9] introduces a computational model based on convolution neural networks to detect N6-methyladenine sites in the rice genome. In the study [10], a model with a custom memory-efficient convolutional neural network (namely RiceNet) is presented for detection of rice grain diseases automatically. In their study, Yang et al. [11] propose an approach to identify the main growth stages of rice from RGB images using convolutional neural network architecture. In their study, Shi et al. [12] propose a collaborative method that combines deep learning and machine learning theory to monitor rice quality variance. In the study [13], a faster region-based convolutional neural network is utilized for the real-time determination of three rice leaf diseases including hispa, brown spot, and, rice blast. The study [14] proposes a method that combines the learning capability of deep learning with the simplicity of phenological methods to map the rice paddy with high accuracy without the requirement of field samples. In the literature, there are also many different studies using deep learning-based classification models, the main subject of which is rice. In the study [15], convolutional neural network is used to classify broken rice and whole rice. In the study [16], a hyperspectral imaging model is presented for the classification of 10 different high-quality rice varieties using a deep learning network. In the study [17], a label-free classification model is proposed for different rice varieties using a deep neural network assisted imaging technique. In the study [18], a deep learning-based method is used to classify both grain-shaped and milled images of five varieties of Spanish rice. In the study [19], a rice seedling image classification model is proposed using a convolutional neural network algorithm. In the study [20], a classification model is proposed using a convolutional neural networks with 18 layers for seven different rice varieties mostly grown in Pakistan. In the study [21], a model is proposed to classify five different types of rice (semi, sd, integ, blanco, vapo) in flour or grain format with a convolutional neural network using thermographic images of rice.

As can be understood from the examples mentioned, studies on the classification of rice in the literature generally consist of the convolutional neural network models in which rice images are used as the training data. In our study, differently, we present a deep neural network model for the classification of rice data. For this purpose, we use the Rice dataset, which consists of numerical equivalents of rice images, details of which are described in section 2.1. In other words, we classify on a data set that includes not the images of rice, but the numerical equivalents obtained from these images. These numerical data consist of morphological data of rice grains obtained by using computer vision from images grains of rice.

2 MATERIAL AND METHODS

2.1 Dataset

In this study, the Rice dataset created by Cinar and Koklu [22], by computer vision of rice grains of Osmancik and Cammeo species native to Turkey is used. In their work, firstly, images of rice samples are obtained and images are processed with image processing techniques. The images are then converted to grayscale images and then binary ones. In the next step, noise removes from the images. In the last step, morphological features are extracted from the acquired images. The Rice dataset consists of numerical values obtained from these morphological characteristics of rice grains. Table 1 shows the morphological features and explanations of the Rice data. Table 2 shows the statistics of the Rice data.

Table 1 The morphological features and explanations of the Rice data

Feature	Explanation
Area	States the number of pixels therein the boundaries of the grain of rice.
Perimeter	Computes the perimeter by reckoning the distance among pixels around the boundaries of the rice grain.
MajorAxisLength	States the longest line that can be drawn on the grain of rice, that is, the big axis distance
MinorAxisLength	States the shortest line that can be drawn on the grain of rice, that is, the small axis distance
Eccentricity	Measures how round the ellipse is, which has the identical moments as the grain of rice.
ConvexArea	States the pixel count of the smallest convex shell of the region created by the rice grain.
Extent	States the ratio of the region created by the rice grain to the bounding box pixels.
Class	Class distribution: 2180 Osmancik, 1630 Cammeo.

Table 2 The statistics of the Rice data

Features	Min	Max	Mean	Std. Dev.	Skewness	Kurtosis
Area	7551	18913	12667.73	1732.37	0.3252	-0.4311
Perimeter	359.1	548.446	454.2392	35.5971	0.2214	-0.8402
MajorAxisLength	145.2645	239.0105	188.7762	17.4487	0.2602	-0.9518
MinorAxisLength	59.5324	107.5424	86.3138	5.7298	-0.1349	0.5621
Eccentricity	0.7772	0.948	0.8869	0.0208	-0.4492	0.0711
ConvexArea	7723	19099	12952.50	1776.97	0.3198	-0.4658
Extent	0.4974	0.861	0.6619	0.0772	0.3438	-1.0301

2.2 Methods

In our study, we compare the performance of the proposed method with the results of the machine learning methods (LR, MLP, SVM, DT, RF, NB, KNN) reported in the study [22], and ensemble methods (AB, BG, VT) reported in the study [23], to classify the Rice data. These methods are briefly described below.

2.2.1. Logistic regression

Logistic regression-LR [24] is a statistical approach that helps to define the relationship between dependent and independent variables and to establish an acceptable model, using the least variable to have the best fit. In its basic form, the dependent variable is estimated from one or more variables using a logistic function. In the binary LR model, a dependent variable has two possible values, such as Osmancik/Cammeo. These values are encoded 0 and 1. Each of the independent variables can be a binary variable or a continuous one.

2.2.2. Multilayer perceptron

Multilayer perceptron-MLP [25] is a type of deep neural network that consists of at least three layers. These layers are the input layer, hidden layer and, output layer. The number of hidden layers varies according to the problem, at least one, and is adjusted according to the need. The output of each layer becomes the input of the next layer. Each node is connected to all nodes in the next layer. The output layer processes data from previous layers and determines the output of the network. The output number of the system is equal to the number of nodes in the output layer.

Cinar and Koklu use an MLP architecture with the most general form in their study [22]. The method proposed in this study is also an MLP. However, it has a much more complex structure than the architecture used in their work. Figure 1 shows the overall architecture of the MLP used in their study.

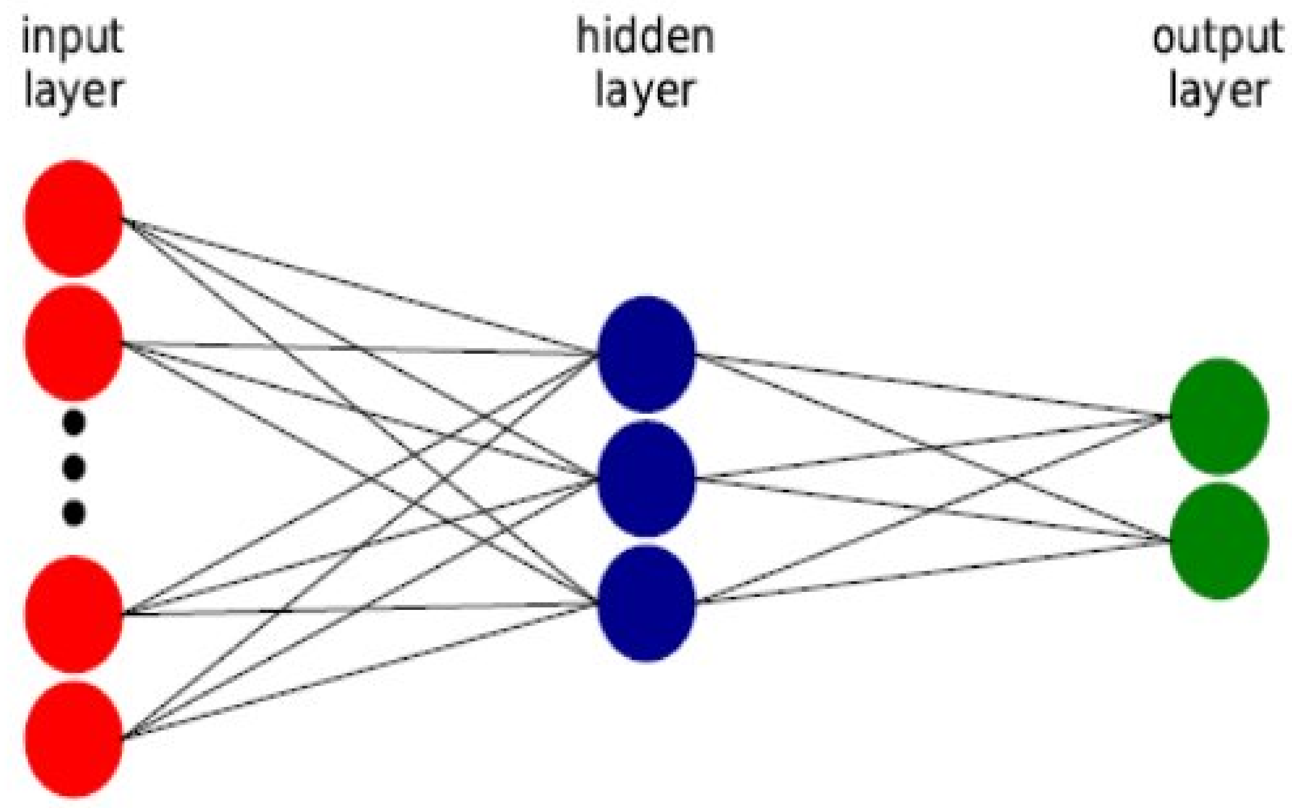

Figure 1: The overall architecture of the MLP

2.2.3. Support vector machine

Support Vector Machine-SVM [26] is a vector space-based machine learning method that finds a decision boundary between the two classes that are furthest from any point in the training data. SVM classifies probability average is the output class is called soft voting. The voting in which the class with the highest number of votes is the output class is called hard voting.

2.3. Proposed method

Our model is a deep neural network consisting of 3 hidden layers and 2 dropout layers (called 3H2D). Deep neural networks are quite robust learning systems. However, overfitting is an important problem for these networks. Because large networks are slow to process, this makes it difficult to deal with overfitting by uniting the estimations of different big neural networks at test time. Dropout [35] is a method to figure out this problem. The main idea behind the method is to randomly drop nodes (with their connections) from the neural network in the training process. This prevents the nodes from fitting too much. In 3H2D we use ReLU (Rectified Linear Unit) activation function in the first hidden layer and the sigmoid activation function in the other hidden layers. The dropout probability of the model set to 0.5. This means that the randomly selected half of the available nodes are disabled where the dropout is applied. The initial random weights of the layers are determined uniform (it generates values with a uniform distribution). Adam is selected as an optimizer with 0.001 learning rate. The activation function of the output layer set to softmax. We train the model with 50 epochs, 5 different batch_size values between 32-512. The best accuracy value is obtained when the batch_size is 32. All these hyper-parameters are chosen intuitively at the beginning and after different trials, the parameters that show the best performance are preferred. Python's Keras library [36] is used in the implementation of the model.

The Mean Square Error (MSE) in Equation 1 is preferred as the loss function. We normalize the data in the range [0-1]. We divide the dataset as 80% training and 20% testing. To reduce variance and overfitting we shuffle the dataset before dividing. A more general model is created as shuffling the data will ensure the training, test, and validation sets represent the overall distribution of the data. We use 10% of the training data for validation during the training phase. It is taken seed as 1 -seed(1)- for the reproducibility of the results.

Where y is the vector of actual values of the variable being predicted, $\hat{y}$ is the predicted values of the variable. Figure 2 shows the architecture of the proposed model.

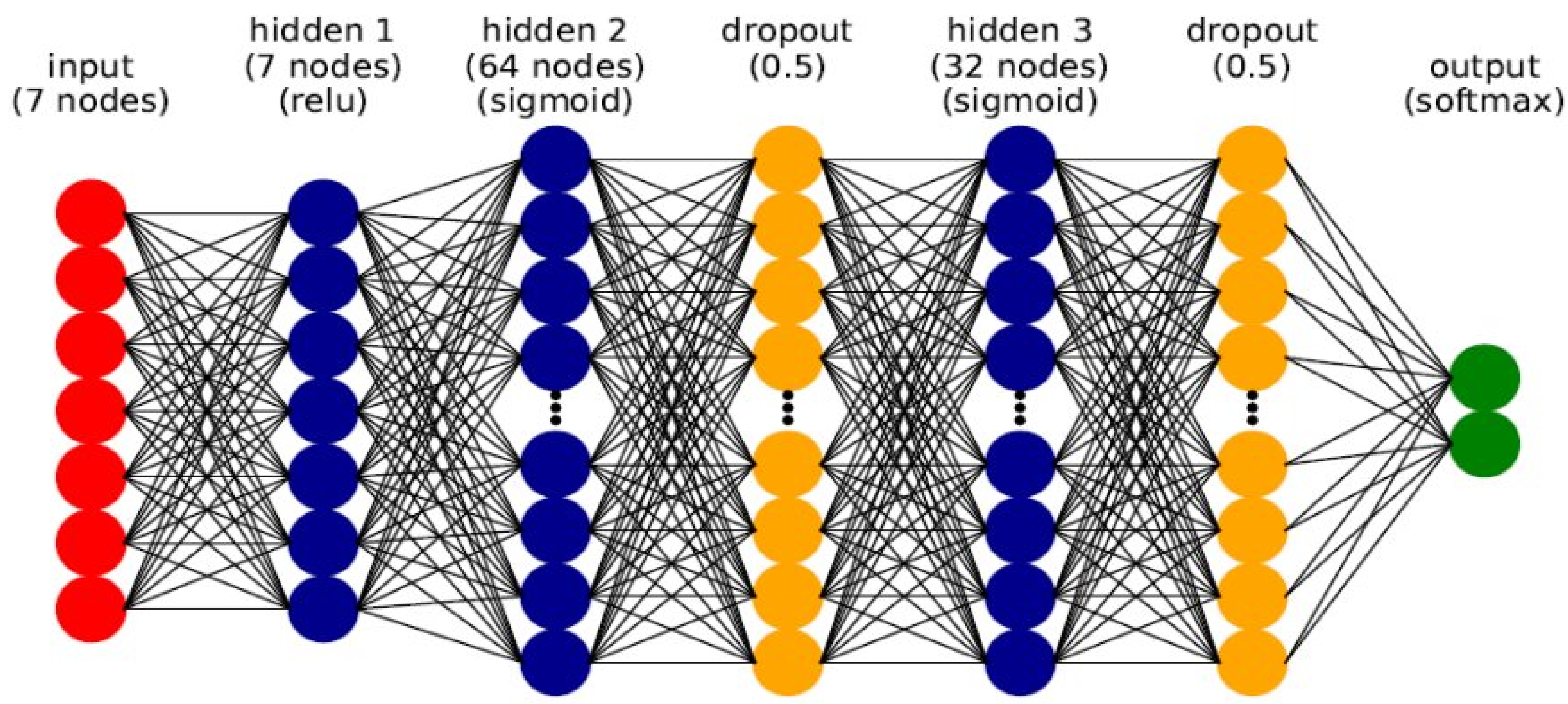

Figure 2: The architecture of the 3H2D

3 RESULTS AND DISCUSSION

In this study, we classify with a deep neural network on the Rice dataset, which includes the Osmancik type grown in run our model with different batch_size values and save the results. Secondly, we compare the highest score of Turkey since 1997 and the Cammeo type grown since 2014. We prefer two ways of classification. First, we our model with 7 different machine learning methods. Batch_size specifies the number of samples to be used to train the neural network at a time. In other words, it is the number of samples used to update the parameters of the network at each step. The larger the batch_size value, the shorter the time required for classification. However, it is quite important to choose the most appropriate value as it directly affects the classification success. In our model, the highest classification accuracy is obtained with 94.09%, when the batch_size value is 32. The time spent by the model for this is 8.57 seconds. When the batch_size value is taken as 512, the classification success decreases to 90.16%, but the time is shortened to 2.14 seconds. From this point of view, it can be concluded that it is possible to shorten the time by increasing the batch_size value for large data sets whose training process will take a lot of time, in a way that will minimally affect the classification success. Table 3 shows the performances of the 3H2D for different batch_size values. Figure 3 shows the learning and loss curves of the 3H2D.

Table 3 The performances of the 3H2D for different batch_size values

Batch_size	**Accuracy %**	**Train_loss**	**Test_loss**	**Time(second)**
32	94.09	0.0613	0.0484	8.57
64	93.44	0.0616	0.0495	5.16
128	93.44	0.0646	0.0501	3.49
256	92.39	0.0715	0.0554	2.74
512	90.16	0.8494	0.0879	2.14

The testing (or validation) loss is smaller than the training loss as we use the dropout regularization layer in our network. Because the dropout mechanism is enabled during the training process but disabled during the testing process. Also, the training error (or loss) of the model is the average of the errors (or losses) for each batch of the training data, throughout the current epoch. On the other hand, the testing error (or loss) for an epoch is calculated at the end of the epoch, resulting in a lower error. Table 4 shows the performance of the proposed method (3H2D) in comparison with LR, SVM, DT, MLP, RF, NB, KNN, AB, BG, and VT. The performance of the models is evaluated in terms of accuracy, precision, sensivity and f1-scor values. Considering the results in Table 4, it is seen that 3H2D has more successful results than all the classification algorithms it is compared to. In Figure 4, it is also possible to see the performance of the models visually. It is clear from the graphs in the figure that the proposed method performs better.

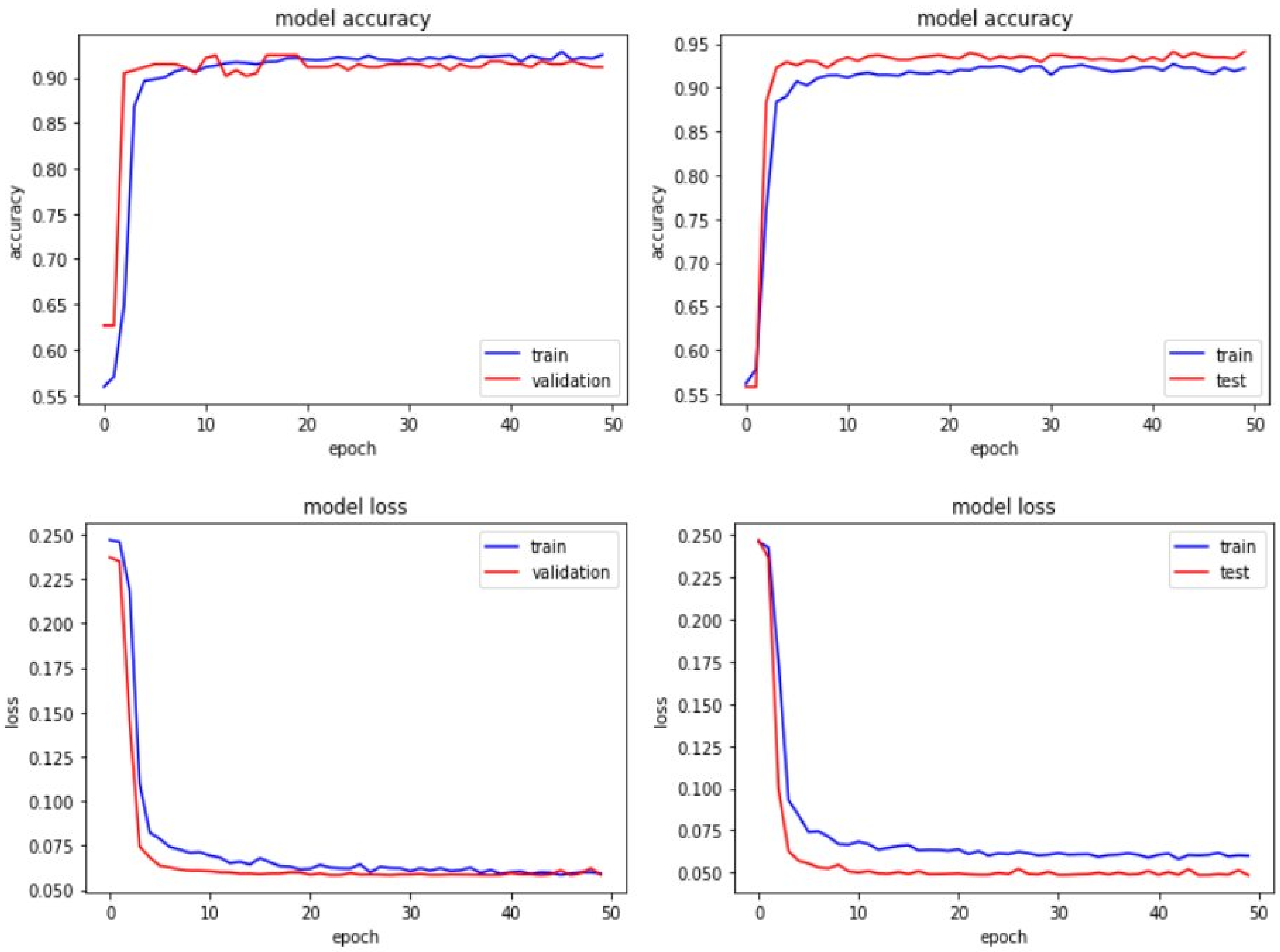

Figure 3: The learning and loss curves of the 3H2D (batch_size=32)

Table 4 The comparative performances of the methods

Method	Accuracy	Precision	Sensivity	F_1-scor
LR	93.02	91.35	92.26	91.80
MLP	92.86	91.04	92.17	91.60
SVM	92.83	91.53	91.70	91.62
DT	92.49	91.29	91.18	91.23
RF	92.39	90.80	91.36	91.08
NB	91.71	89.63	90.86	90.24
KNN	88.58	87.06	86.37	86.71
AB	92.34	92.18	92.16	92.17
BG	91.68	91.47	91.55	91.51
VT	90.52	90.40	90.22	90.30
3H2D	94.09	93.71	92.87	93.29

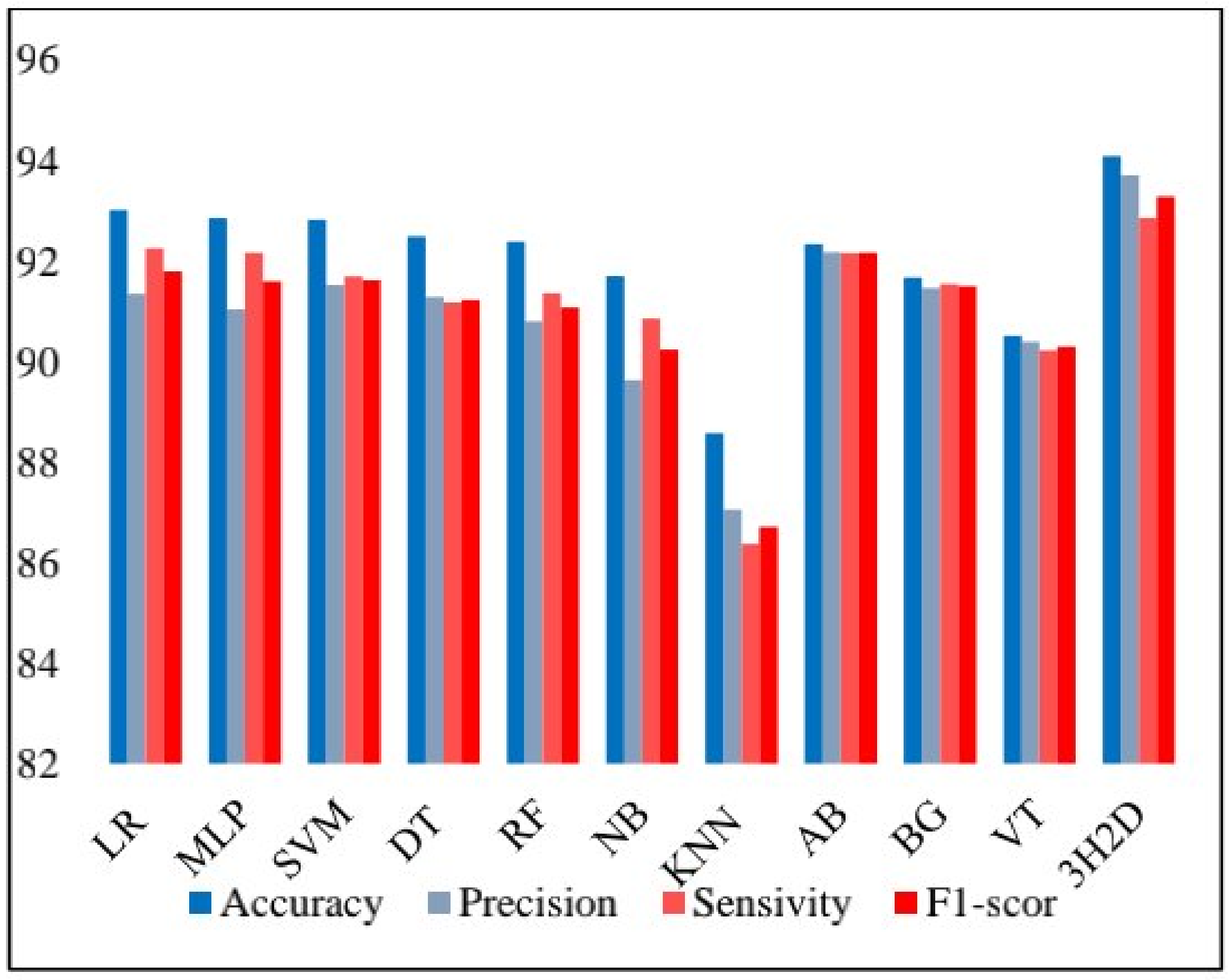

Figure 4: The performances of the models

4 CONCLUSION

In this study, we classify two rice varieties that have been patented in Turkey, with a model we created using deep neural networks. The network model we use consists of 3 hidden layers and 2 dropout layers. The purpose of adding the dropout layers is to avoid overfitting problem in classification. We compare our model (3H2D) with 10 different machine learning algorithms using accuracy, precision, recall and f1-score metrics. Among the other machine learning algorithms, LR achieves the best classification success with 93.02%. On the other hand, the classification success of the proposed method is 94.09%. The obtained results reveal that our model, called 3H2D, outperforms all machine learning algorithms it is compared for all metric values. In addition, the proposed method has a very flexible and useful model. It is also functional to use it for datasets that have multi-class or from different fields by changing its hyper-parameters.

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