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A Study of Ensemble Deep Learning Method Using Transfer Learning for Horticultural Data Classification

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Abstract

Deep learning is an important discipline in which human-specific problems are solved with the help of machines with advanced hardware power. It is seen this discipline is widely used in the fields of industry, health, defense industry, and sports. In addition, the use of deep learning in the field of horticulture is an important requirement. With the integration of deep learning into horticulture, to do product classification is very important for increasing productivity and production.

In this study, a method using ensemble learning is proposed to improve the accuracy of the classification problem for horticultural data. For this method, a new dataset was created, containing a total of 24421 images and 15 crop classes, independent of data augmentation. In order to train this created data set with the help of the proposed method, a hierarchical structure has been designed in which the output of one model is the input of the other model. A total of 7 pre-trained models were used in the experimental studies of the proposed method. Since this method is in an ensemble structure, it is possible to add or remove pre-trained models from the structure. With the help of experimental studies, a performance analysis of the proposed method, which is compared with the traditional CNN method, has been made. As a result of these analyses, it has been observed that the proposed method works 3% more successfully.

Keywords: Transfer learning, ensemble learning, convolutional neural network, image classification, deep learning.

Bitki Sınıflandırması için Transfer Learning Kullanılarak Topluluk Öğrenmesi Metodu Üzerine Bir Çalışma

Öz

Derin öğrenme, insana özgü problemlerin gelişmiş donanım gücüne sahip makineler yardımıyla çözüldüğü önemli bir disiplindir. Bu disiplinin sanayi, sağlık, savunma sanayi ve spor alanlarında yaygın olarak kullanıldığı görülmektedir. Ayrıca bahçecilik alanında derin öğrenmenin kullanılması önemli bir gerekliliktir. Derin öğrenmenin bahçeciliğe entegrasyonu ile ürün sınıflandırması yapmak, verimliliği ve üretimi artırmak için oldukça önemlidir.

Bu çalışmada çeşitli bitki verilerini kullanarak sınıflandırma probleminin doğruluğunu artırmak için topluluk öğrenmesi yöntemi önerilmiştir. Bu yöntem için veri artırmadan bağımsız olarak toplam 24421 görüntü ve 15 ürün sınıfı içeren yeni bir veri seti oluşturulmuştur. Önerilen yöntem yardımıyla oluşturulan bu veri setini eğitmek için bir modelin çıktısının diğer modelin girdisi olduğu hiyerarşik bir yapı tasarlanmıştır. Önerilen yöntemin deneysel çalışmalarında toplam 7 adet önceden eğitilmiş model kullanılmıştır. Bu yöntem bir topluluk yapısında olduğu için yapıya önceden eğitilmiş modeller eklemek veya çıkarmak mümkündür. Deneysel çalışmalar yardımıyla önerilen yöntemin geleneksel CNN yöntemi ile karşılaştırılan performans analizi yapılmıştır. Bu analizler sonucunda önerilen yöntemin %3 daha başarılı çalıştığı görülmüştür.

Anahtar kelimeler: Transfer öğrenme, topluluk öğrenme, evrişimli sinir ağı, görüntü sınıflandırma, derin öğrenme.

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1. Introduction

With the development of artificial intelligence technologies, human-specific problems become the subject of machines. Artificial intelligence techniques combined with machines are driving technological developments in many areas such as speech recognition, visual object recognition, object detection, disease diagnosis, and gene sequence classification. In many studies on deep learning, which is a sub-discipline of artificial intelligence, researchers have offered various solutions to reach the most accurate result with different methods (LeCun et al., 2015). The classification problem is one that artificial intelligence can solve on a large scale. Although various traditional deep learning algorithms continue to work on this problem, the realization of accuracy and speed improvements is an important issue.

The most important source of information in machine learning and deep learning projects is data. Where data source is few, or data collection is difficult, pre-trained models with more easily collected data are needed. These models, which were previously trained with large data sets and whose weights are generally accepted, are called SOTA (State-of-the-Art) models, and this method is called transfer learning. Transfer learning is a method that has been tried many times and has proven itself in this field (Weiss et al., 2016, Babu &Annavarapu, 2021, Altaf et al., 2021, Salama & Aly, 2021, Vidal et al., 2021). Transfer learning is very advantageous compared to creating a new model since the precision of the results is not known when creating a model network and it requires many trials. Classification of horticultural products is an important field of study in which artificial intelligence technologies can be used. Using more than one different model together is a method called ensemble learning, which increases the accuracy of the model. With this learning method, in which the results of several models are analyzed together without depending on a single model, more reliable and accurate predictions are obtained (Re & Valentini, 2014). Ensemble learning can be adapted to classification and regression problems using different algorithms.

In this study, a structure in which more than one model is used together is proposed in order to solve the classification problem and increase its accuracy. This structure is designed to use different models together and the output of one model forms the input of the other model. These models, which were trained using transfer learning with a total of 24421 images, were used to classify 16 different classes. Performance analyses of the proposed method were carried out on the created data set and the results were presented in detail. In addition, the proposed structure was compared with the traditional CNN (Convolutional Neural Networks) classification method, and precision, recall, and f1score values were measured.

2. Related Works

When the literature is examined, many studies using the transfer learning method, seem to focus on images, especially radiography, etc. The most important reason for this is that medical data sets consist of accessible data. However, although there are difficulties in collecting data, studies in the field of horticulture have also been encountered. Studies in both scientific fields focus on the comparison of many common scientific methods, regardless of the differences in data sets.

For the classification of horticultural data, many studies have been carried out and different methods have been used so far (Yang & Xu, 2021, Palaparthi et al., 2023).

Abed et al., using a dataset with 1295 images and 3 classes to increase productivity in horticulture, detected disease on bean leaves. In this determination, they measured the performances of more than one pre-trained model and compared the accuracy, selectivity, f1score, and AUC (Area Under the Curve) values. Among the pre-trained models compared, DenseNet121 gave the best result with an accuracy of 98.31% (Abed et al., 2014). Zhao et al. created an object detection algorithm using deep learning with the images they obtained with the help of unmanned aerial vehicles in order to use artificial intelligence in the field of modern horticulture. Using the pre-trained YOLO v3 model, a bale detection algorithm was created on the labeled data. It was observed that detection performance increased in the model they trained using approximately 243 images (Zhao et al., 2021). In their study, Garcia et al. proposed an artificial intelligence assistant model in which both deep learning and traditional machine learning algorithms are combined for the classification of horticultural plants. For the test of the created model, two crops and two weed groups were selected, a unique data set was created, and performance analyzes were demonstrated (Garcia et al., 2020). Dawai et al. used transfer learning to detect pests in order to increase productivity in horticulture. This model, which can predict a total of 10 classes, reached an accuracy of 93.84% (Dawei et al., 2019). Kang and Gwak were used to classify the freshness of fruit, which is an important issue in horticulture. They proposed an ensemble learning model in which multi-task deep convolutional neural networks based on ResNet50 and ResNet101 architectures are used together. The proposed method has reached high accuracy values (Kang and Gwak, 2021).

Weed and product classification in horticulture is an important issue for increasing productivity and production. It is seen as a result of the literature review that the concepts of transfer learning and ensemble learning give very good results in this regard (Garcia et al., 2021, Bosilj et al, 2019, Yang et al., 2019). Xie et al. used transfer learning to measure the quality of the produced product and detected defective products in the carrot vegetable they selected as an example. In their study, they used 5 different state-of-the-art models and the ResNet50 model gave the best result. With the ensemble learning method, in which the ResNet50, Densenet121 and VGG16 models, which they created in order to increase the accuracy, are used together, they have reached 97.32% accuracy (Xie et al, 2021). Jahanbakhshi et al. developed a CNN structure using the stochastic pooling mechanism to detect and classify the apparent defects of sour lemon fruit. In order to perform these performance analyses, a unique data set with images of healthy and damaged sour lemon fruit has been created. They compared their work with other machine learning algorithms such as KNN (K-Nearest Neighbors), SVM (Support Vector Machine), ANN (Artificial Neural Networks), and DT (Decision Tree) (Jahanbakhshi et al, 2020).

Ensemble learning, which is a learning method where several different models are run at the same time and results are obtained, is frequently used in image classification. Ganaie et al. explained ensemble learning comprehensively in their study and provided information on its use in different fields (Ganaie et al., 2021). Ahmad et al. used the ensemble learning method, which combines the attributes of different models to solve the classification problem. In their study, it was observed that the combined use of MobileNet and InceptionV3 models made better classification than their separate use (Ahmad et al., 2021). ResNet50 and SSDMobileNetV2, which are state-of-the-art models, are frequently used in transfer learning. In many studies, the performance values of these two models are shown in detail (Linguo et al., 2021, Biswas et al., 2018, Shabir et al, 2021, Li et al 2018).

Considering these studies in the literature, in classification problems; It is seen that transfer learning and ensemble learning methods are frequently used. In this study, a different classification architecture is proposed using these 2 methods. The structure of this classification architecture, which aims to increase accuracy compared to traditional methods, is explained and performance data are measured and compared with different models. To the knowledge of the authors, the proposed architecture has not been done before.

3. Material Method

Transfer learning and fine-tuning have been used to compare the success of the proposed method with traditional methods. In order to perform transfer learning, one of the pre-trained models, ResNet50, was first applied to all layers. Then, the study was evaluated by using MobileNetV2 models, which are faster but less successful than ResNet50, in order to evaluate the performance. MobileNetV2 model is fast due to the basic parsing in the first layer. In the other layers, a new ensemble learning has been created by choosing ResNet50 to increase the result performance.

3.1. Dataset

All of the images included in the database in this study were compiled and used via Kaggle (Kaggle, 2022). Within the scope of the study, a total of 24421 images were used and these images were divided into 4 clusters as in Figure 1. There are 4 different classes in mushroom, flower, and fruit clusters, and there are 3 classes in vegetable clusters.

While 24421 images in the data set were used to train the proposed method, 100 different new images were preferred for the test of the model. In addition, 80% of the training data set is presented to the learning algorithm as train and 20% as validation in order for the model to produce more meaningful results. Sample images from the train and validation data are presented in Figure 2. Within the scope of the study, the amount of data of each class was taken as approximately 2000 in order to prevent the problem of bias in the model depending on the number of data of the classes. The data counts of the classes away from this reference were matched using data augmentation.

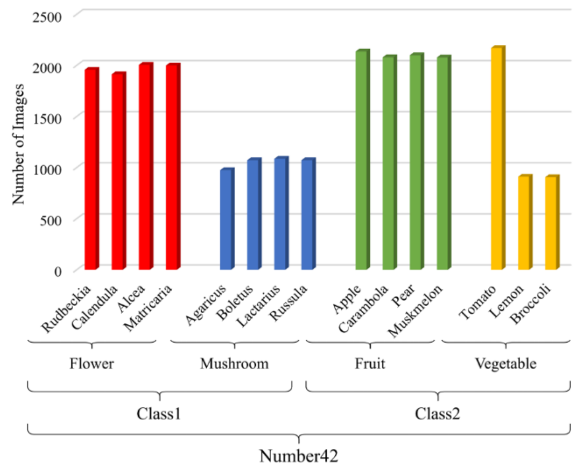

Figure 1. Distribution of data belonging to classes

In order to compare the proposed method with the models used in traditional CNN methods, a data set consisting of 4 clusters and 15 classes was prepared. In order to avoid bias in the prepared data set, the data augmentation method was applied to the classes with few visuals (Brocoli, Lemon, Agaricus, Boletus, Lactarius, Russula). In order to increase the number of images they contain, the mirroring method has been applied to the classes to which the data augmentation process has been applied, and it is aimed to double the number of images they contain. Thus, a total of 30,494 images were obtained. The dimensions of the images are scaled to be 224x224 pixels and 3 channels. When the graphics card and memory usage are taken into consideration, the batch method is used in order to shorten the processing time. A total of 953 packages were created, with 32 images in each package, and 80% of the entire data set was divided into the train (Figure 2.a) and 20% validation (Figure 2.b).

(a) (b)

Figure 2. a) Train dataset visual, b) Validation dataset visual

3.2. Proposed method

Convolutional neural networks consist of two basic layers: convolutional and fully connected. The input data is first subjected to filtering and activation functions in the convolutional layer. At this stage, various pooling methods and normalization operations are performed to extract the attribute features of the input data. The input data from which the feature is extracted is made into a one-dimensional array in the flattening layer. Then, the flattened data is passed to the fully connected layer, where all neurons are interconnected for classification, and the convolutional neural network model is formed. In traditional CNN classification, more than one class is tried to be estimated using a single model. In this process, the precision of estimating a class decreases, and the success rate of the model decreases if the number of classes is large or the similarity between classes is intense.

In this study, a method is proposed in which models created with CNN structure are used together in order to increase the success of the traditional classification process. The working system of the proposed method, whose pseudo-code is given in Table 1, is based on the concept of an ensemble of models. In the proposed method, a total of 7 models were used together, with the output of one model forming the input of the other model.

Table 1. Pseudo code of proposed method

```
Algorithm
for image, labels in iterate the test data:
    for a=1:100 do:
        reshape of image[a]
        predict image with model_number_42
        select max index in class names of model_number_42
        if model of layer_1_pred equals to 'class1':
            if model of class1_2_pred equals to 'Flower':
                add flower_3(image) to predictions list
            else:
                add mushroom_3(image) to predictions list
        else:
            if model of class2_2_pred equals to 'Fruit':
                add fruits_3(image) to predictions list
            else:
                add vegetables_3(image) to predictions list
```

The proposed method consists of 3 layers as shown in Figure 3, and the first layer is named Number42, which is one of the important names that D. Adams brought to the literature (Adams, 1979). In the study, the Number42 model predicts 2 classes named Class1 and Class2. These classes are grouped according to the similarities of the classes in the 3rd layer. Models predicting classes in layer 3 are named after Class1 and Class2. Finally, the classification is completed when the models in the 3rd layer predict the output classes.

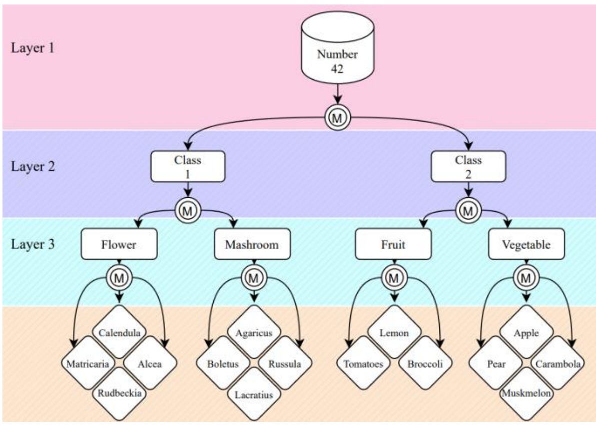

Figure 3. Proposed method structure (M: Pre-trained model)

3.3. Fine tuning

In artificial neural network models, the loss function must be at a minimum level for learning to function properly. Various optimization algorithms are used to minimize the loss function. In this study, ADAM (Adaptive Moment Estimation), which is one of the optimization algorithms frequently encountered in artificial neural network training, was used as a loss function, and Sparse Categorical Crossentropy was used. The w_t value in the ADAM optimization algorithm, whose formulation is given in Equation 1, represents the updated weight. The m_t represents bias corrected versions of moving averages. vt is the sum of the squares of the gradients up to time t. The learning rate, on the other hand, was taken as 0.001 by showing the symbol n. The ADAM function is found by multiplying the learning value for the weight update with the gradient of the function and subtracting it from the previous weight. In the fully connected layer of the neural network, the Global Average Pooling method is preferred instead of the flattened layer in order to increase the computational performance. In order to reduce overfitting, 3 dropout layers were added to the study and the coefficient was taken as 0.3, valid for all models. All artificial neural network models were created by activating the GPU on Google Colab in order to measure the success of the experiment and control the process independently from the hardware.

$$w_t = w_{t-1} - n\frac{m_t}{\sqrt{v_t}+\in} \quad (1)$$

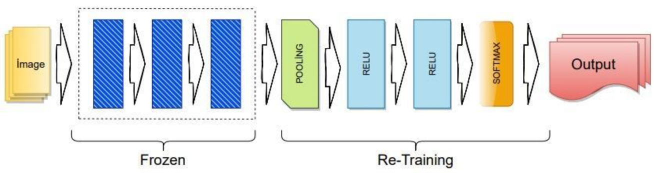

Figure 4. Pre-trained model diagram

As shown in Figure 4, while using the pre-trained models with optimum weights for retraining, a certain part of them is frozen. This process saves time and provides a performance increase.

3.4. Performance evaluation

Different evaluation metrics are used to see the performance of the proposed approach for the classification problem. The effectiveness of the proposed approach was measured and compared with the traditional CNN approach. The evaluation metrics used Accuracy (ACC), Precision (P), Recall (R), and $f_1$score (f_1) are shown in the Equation. (2-5). The fact that the results obtained from these metrics are close to 1 indicates that the model is a successful one.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

$$f_1score = 2 + \frac{P*R}{P+R} \quad (5)$$

TP, TN, FP, and FN; represent the True Positive, True Negative, False Positive, and False Negative prediction numbers, respectively.

4. Results

In this study, a structure has been considered in order to increase the accuracy compared to traditional methods and a method has been proposed in this direction. The proposed method is designed in such a way that the output of one model is the input of the other model by using the models one after the other. ResNet50 and MobileNetV2 models were used both together and separately to perform the performance analysis of the proposed method. In order to compare, a total of 3 experimental studies were conducted, 2 of which worked with the proposed method and the other with the traditional CNN method. The structure called 1Mob23Res, prepared with the proposed method, was designed using MobileNetV2 models in the 1st layer and ResNet50 models in the 2nd and 3rd layers. In another experimental study of the proposed method, the ResNet50 model was used in all layers of the structure called 123Res. In addition to these two experimental studies of the proposed method, CNN, which is the conventional image classification method, was used alone in the third experimental study. In the last experimental study, the CNN structure was performed using the pre-trained ResNet50 model called SM1. Comparative results of these experimental studies are given in Table 2. In the experiments, 100 test data prepared in accordance with the data set were used and the numerical distribution of the test data over the classes. In order to decide whether the proposed method is successful or not, the P, R and f1score values observed in the experiments were examined separately for each test data in Table 2. As a result of the studies, it was observed that the average ACC values of the 1Mob23Res and 123Res experimental studies were equal. Although ACC values are equal in these two experimental studies, there are differences for each class. For example, while P, R and f1score values are [0.50 1 0.67] in the 1Mob23Res structure of Lemon test data, this situation is observed as [0.45 1 0.62] in 123Res structure. In the calendula test data, this situation was observed as 1Mob23Res [0.78 1 0.88] and in the 123Res structure [1 1 1]. Lemon test data was better predicted by 1Mob23Res, but Calendula test data outperformed 123Res. In addition, the results of the comparison of the proposed method with SM1 are given in Table 2 on a class basis. The prediction performance in Tomatoes test data was observed as [0.50 0.14 0.22] in the 1Mob23Res and 123Res structures, while it was [0 0 0] in the SM1 structure. Therefore, the traditional CNN model, SM1, failed to predict the Tomatoes test data. From the experimental studies performed with the proposed method, 1Mob23Res and 123Res structures reached 83% ACC, while SM1 conventional CNN reached 80% ACC. As a result, the success rate of the proposed method is 3% better than the traditional method. In order to train the proposed method, a data set consisting of 24421 images was used, and for the test of the model, 100 new images were preferred, independent of the training data set. As a result of the experiments performed with these test data, although the ACC performance rates are equal, the time taken for the estimation of the classes is different from each other in both experimental studies. While the prediction times were 45.368 seconds for 1Mob23Res, this value was 49.001 seconds for 123Res. It has been observed that the prediction time of the traditional CNN classification model (SM1) is 36,729s for this data set. This shows that the 1Mob23Res experimental study performed with the proposed method makes 19.02% slower estimation compared to the traditional method.

Table 2. Classification report by evaluation metrics, (P, R, and f1 represent precision, recall, and f1 score, respectively.)

	Multi-model								
	1Mob23Res			123Res			SM1		
	P	R	f_1	P	R	f_1	P	R	f_1
Agaricus	0.83	0.83	0.83	0.83	0.83	0.83	1.00	0.83	0.91
Alcea	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Apple	0.75	0.43	0.55	0.75	0.43	0.55	0.75	0.43	0.55
Boletus	1.00	0.83	0.91	1.00	0.83	0.91	0.80	0.67	0.73
Broccoli	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Calendula	0.78	1.00	0.88	1.00	1.00	1.00	0.88	1.00	0.93
Carambola	1.00	0.33	0.50	1.00	0.33	0.50	1.00	0.33	0.50
Lacratius	0.88	1.00	0.93	0.88	1.00	0.93	0.86	0.86	0.86
Lemon	0.50	1.00	0.67	0.45	1.00	0.62	0.41	1.00	0.58
Matricaria	0.86	1.00	0.92	0.86	1.00	0.92	1.00	1.00	1.00
Muskmelon	0.86	1.00	0.92	0.86	1.00	0.92	1.00	1.00	1.00
Pear	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Rudbeckia	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Russula	1.00	0.83	0.91	1.00	0.83	0.91	0.62	0.83	0.71
Tomatoes	0.50	0.14	0.22	0.50	0.14	0.22	0.0	0.0	0.0
ACC			0.83			0.83			0.80
Macro avg	0.86	0.83	0.82	0.87	0.83	0.82	0.82	0.80	0.78
Weighted avg	0.85	0.83	0.81	0.86	0.83	0.81	0.81	0.80	0.78

Since the proposed method in future studies is in an ensemble structure, it can be easily run with similar models such as InceptionV3, VGG16, and Efficient without any structural changes, and performance analyses can be evaluated with the same or different data sets. Similarly, by changing parameters such as the number of layers and classes, performance values such as accuracy, precision and f1score can be compared. When the number of data is increased, it is predicted that the proposed method will give more accurate results compared to the traditional method. Experiments with the method proposed in this study in the field of transfer learning will carry the study further.

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