A Model-Based Deep Transfer Learning Algorithm for Phenology Forecasting Using Satellite Imagery

M. Á. Molina, M. J. Jiménez-Navarro, F. Martínez-Álvarez, and G. Asencio-Cortés(✉)

Data Science and Big Data Lab, Pablo de Olavide University, 41013 Seville, Spain
{mamolcab,mjjimnav}@alu.upo.es, {fmaralv,guaasecor}@upo.es

Abstract. A new transfer learning strategy is proposed for classification in this work, based on fully connected neural networks. The transfer learning process consists in a training phase of the neural network on a source dataset. Then, the last two layers are retrained using a different small target dataset. Clustering techniques are also applied in order to determine the most suitable data to be used as target. A preliminary study has been conducted to train and test the transfer learning proposal on the classification problem of phenology forecasting, by using up to sixteen different parcels located in Spain. The results achieved are quite promising and encourage conducting further research in this field, having led to a 7.65% of improvement with respect to other three different strategies with both transfer and non-transfer learning models.

Keywords: Transfer learning · Deep learning · Classification · Pattern recognition

1 Introduction

The agricultural sector has historically positioned itself as the most important economic sector as it provides the basic livelihood for the population. In recent years, due to a growing world population, increased crop security and climate change, this sector is undergoing strict production controls that are driving up production costs and therefore prices. This is why new technologies are becoming essential to keep track of all this and provide a fundamental aid for the farmer's decision making.

To this end, it is becoming increasingly widespread to take data on crops and to make use of the information provided by these data. However, this data collection is a very recent development and there is still not enough historical information available to allow the application of traditional machine learning techniques.

For this reason, it is necessary to apply new techniques that allow the optimal treatment of this data and to use the existing general information in geographical

H. Sanjurjo González et al. (Eds.): HAIS 2021, LNAI 12886, pp. 511–523, 2021.
https://doi.org/10.1007/978-3-030-86271-8_43

areas where information is still scarce. New deep neural network techniques typically require a very large data history and, consequently, a long time before they can be applied. In these cases, there is a need of widening the knowledge base by extracting information from additional datasets.

The integration of deep learning [1,2] with transfer learning is called deep transfer learning and it makes the most of both paradigms. Thus, deep learning is used to model problems within big data contexts and, afterwards, re-purposed to transfer the knowledge to models with insufficient data [3]. There is a major flaw in transfer learning, which is the lack of interpretability of its models because pretrained models are applied to the new data without any prior information or understanding of the model [4].

A new transfer learning strategy is proposed in this work, based on the application of a convolutional neural network (CNN). In particular, a 8-layer CNN is trained with the source dataset. Then, the last two layers are retrained with a training set from the target dataset. Different training sets, as explained in Sect. 3, are created in order to validate the robustness of the method.

To assess the performance of the proposal, sampling data from phenological stages in different olive grove plots and satellite index data (obtained from images) have been used. However, any other problems could be used to evaluate the goodness of this general-purpose methodology. This dataset is formulated as a classification problem, in four phenological states. Three additional strategies are also evaluated to compare the performance in terms of accuracy. The results achieved are quite promising.

The rest of the paper is structured as follows. Section 2 overviews recent and relevant papers in the field of deep transfer learning and its application to classification datasets. Section 3 describes the proposed methodology Sect. 4 reports and discusses the results achieved. Finally, Sect. 5 summarizes the conclusions.

2 Related Works

Deep transfer learning is becoming one of the research fields in which much effort is being put into [5].

In fact, many applications can be found in the literature currently. However, these techniques are not yet widespread in agriculture sector. Some works have been published introducing these techniques. For example, the one described in [6] where basic algorithms are used to yield predictions, disease detection or crop quality, for example.

It should be noted that this work is a continuation of the experiments started in [7], where the same techniques were applied to a group of images of cells affected or not by malaria.

In [8], deep learning techniques are applied to detect phenological stages of the rice crop through images taken by aerial vehicles to make estimates of production and harvest dates.

Transfer learning techniques have also been applied to the agricultural sector for crop type detection in different regions with limited access [9]. Finally, more advanced techniques such as image-based deep transfer learning have been used for disease detection in crops, as can be read in [10]. Papers explaining how transfer learning techniques work can be found at [11,12].

Many applications relate deep transfer learning with remote sensing problems. In 2016, Xie et al. [13] proposed the use of deep transfer learning techniques on satellite images or another type of sensor with the aim of extracting the most information from the available data on issues of food security or sustainable development.

Also, a transfer learning application for scene classification with different datasets and different deep learning models can be found in [14]. The authors analyzed how the setting up of CNN hyperparameters can influence the transfer learning process. They concluded that, contrary to expectations, transfer learning from models trained on more generic images outperformed transfer learning from those trained directly on smaller datasets.

The inclusion of distance studies in works with deep transfer learning techniques are important in order to see the effects or not of datasets similarity. Thus, in [15] some time series are classified using a distance based approach.

3 Methodology

This section first describes the data preprocessing in Sect. 3.1. Section 3.2 details how source and target datasets have been created. The deep neural network architecture is discussed in Sect. 3.3. The validation schemes are introduced in Sect. 3.4. Finally, Sect. 3.5 is devoted to analyze how the clusters shape may affect the model.

3.1 Data Preprocessing

The first step in the data preprocessing is to link the data of the ten bands obtained from the satellite images and phenology (study of changes in the timing of seasonal events such as budburst, flowering, dormancy, migration and hibernation) data of each parcel (a tract or plot of land). Once we have the dataset with the information of all parcels, the information is transformed in order to relate past events with the phenology of the parcel. In this work, the objective is to predict the phenology of each parcel seven days ahead, so the obtained relations between input and output are oriented in that way.

The second step of the preprocessing is to encode the data labels, in order to have as many outputs of the neural network as data labels. Thus, a predicted probability is returned for each label.

3.2 Creation of Source and Target Subsets

Disjoint source and target subsets of data were extracted from the original dataset. The source subset is the dataset from which the initial model was trained. The target subset is the dataset used both to update such model (transfer process) and to test the updated model.

To extract the source and target subsets, it has been tried that such datasets were as different as possible. Additionally, the source subset is larger than the target one. The idea underlying this strategy is to check if the transfer learning is effective when the source and target subsets contain dissimilar information, comparing when the information is similar, and the target set is a smaller one.

For this purpose, a hierarchical clustering was applied to each different label using such table as input. A dendrogram was generated for each label after applying the hierarchical clustering.

Finally, the first three nodes of the second level of the dendrogram were selected. As will be explained later, these three clusters will be used to build the source subset. Each scheme will be tested for each parcel, being a campaign (season) of each one the target subset.

It can be concluded that source subsets were generated in such a way that they contain dissimilar and similar parcels in order to obtain certain results and the source subset is larger than the target subset.

3.3 Deep Neural Network Architecture

The next step consists in training a neural network and testing it using the subsets described in the previous section. The way these subsets are divided to validate the methodology will be explained in the next subsection.

The deep neural network is composed of six dense and fully-connected layers of the network. The last two layers are the layers used to adapt the neural network in transfer learning schemes as it is indicated in last column in Table 1.

The neural network proposed has $14,069$ parameters to be adjusted. The detailed network used is shown in Table 1. To implement the neural network architecture, Keras 2.2.4 over TensorFlow 1.14 was used [16].

Table 1. Deep neural network architecture used for transfer learning.

Layer (type)	Output shape	Parameters	Used for transfer learning
Dense	(None, 115)	2,760	No
Dense	(None, 70)	8,120	No
Dense	(None, 35)	2,485	No
Dense	(None, 15)	540	No
Dense	(None, 8)	128	Yes
Dense	(None, 4)	36	Yes

3.4 Novel Validation Schemes Proposed

Four schemes will be executed for each parcel, so the next explanation is valid for each one. In each experiment, each parcel will be the target subset.

The target subset is divided into two parts: test (last campaign) and training (the remaining campaigns). Fixing the same test part of the target subset provided a fair comparison in each of the four different validation schemes have been proposed.

Scheme 1. The model is generated using the training part (campaigns of each parcel except the last one) of the target subset, and it is tested by evaluating its predictions over the test part (last campaign of each parcel) of the target subset.

Scheme 2. Three schemes are proposed for each parcel in order to prove the effectiveness of the transfer learning techniques.

First, the scheme 2.1. In this scheme, the steps are the following: First, the model is trained using the parcels of the same cluster of the target parcel. Then, such model is updated using the training part (all campaigns of this parcel except the last one) of the target subset. This updating process only optimizes the weights within the two last layers of the neural network, maintaining the rest of its layers without changes. Finally, the updated model is tested by evaluating its predictions over the test part (last campaign) of the target subset.

In the next two schemes, different source subsets are used using the other two clusters in order to show the goodness of transfer learning techniques using dissimilar subsets (belonging to the same branch of the tree or the other one).

In scheme 2.2, the source subset which we train the model is the cluster on the right of the cluster of the target parcel viewing the dendrogram. The steps are the same of the Scheme 2.1.

In scheme 2.3, the source subset which we train the model is the remaining cluster. The steps are the same of the Scheme 2.1.

For each scheme, the methodology has been tested up to 10 times, obtaining very similar but different tests due to the own network characteristics.

3.5 Intra-cluster and Inter-cluster Analysis

Finally, an analysis has been conducted to prove how the effectiveness of the proposed transfer learning methodology varies depending on the distance between parcels classified in the own and another clusters.

For such purpose, the dendrogram obtained with the hierarchical cluster throws the clusters which we are going to use showing the similarity between them depending on the branch to which they belong. The intra-cluster distance is calculated as the average of the distance between the own parcels.

4 Experimentation and Results

This section presents and discusses the results achieved. Thus, Sect. 4.1 describes how the dataset has been generated and interpreted. The metric used to evaluate the performance of the proposal is introduced in Sect. 4.2. The experimental settings are listed and discussed in Sect. 4.3. Finally, the results themselves are reported and commented in Sect. 4.4.

4.1 Dataset

The set of images used to perform the methodology explained in previous section have been taken from two different sources of data.

Table 2. Domains characteristics.

Code	Region	Coordinates	Altitude	Surface	Slope	Soil	Density	Main variety
P01	Jaén	37.71, −2.96	700	6.02	2	Irrigated	178	Picual
P02	Jaén	37.68, −2.94	700	2.86	5	Irrigated	200	Picual, Marteño
P03	Jaén	37.66, −2.93	700	1.09	1	Irrigated	140	Picual, Marteño
P04	Cádiz	36.86, −5.43	360	8.54	19	Dry	58	Lechín, Zorzaleño, Ecijano
P05	Cádiz	36.87, −5.45	770	2.26	19	Dry	138	Lechín, Zorzaleño, Ecijano
P06	Cádiz	36.94, −5.25	350	1.04	5	Dry	134	Picual, Marteño
P07	Cádiz	36.94, −5.30	425	3.10	11	Dry	74	Lechín
P08	Córdoba	37.44, −4.69	280	6.30	1	Dry	194	Picual, Marteño
P09	Córdoba	37.67, −4.33	300	42.53	3	Irrigated	154	Picual, Marteño
P10	Córdoba	37.60, −4.42	460	9.58	9	Dry	76	Picual, Picudo
P11	Córdoba	37.44, −4.71	320	19.52	1	Irrigated	208	Manzanillo
P12	Jaén	37.67, −2.91	700	0.96	3	Irrigated	92	Picual
P13	Sevilla	37.05, −5.01	600	1.93	15	Dry	119	Picual, Marteño
P14	Sevilla	37.10, −5.04	460	31.59	15	Irrigated	156	Manzanillo
P15	Sevilla	37.05, −5.08	520	1.78	20	Dry	120	Hojiblanco
P16	Sevilla	37.07, −5.06	510	2.87	25	Dry	150	Hojiblanco

On the one hand, the information of index and bands (multi-spectral data with 12 bands in the visible, near infrared, and shortwave infrared part of the spectrum) has been collected of the Sentinel satellite images. This satellite captures images from 2015 increasing the sampling rate since then. Now, an image is captured each 4 or 5 days (from 15 days on average in 2015). From these images, different indexes and the values of the colour bands are calculated for each pixel of the image. In this work, the mean value of the pixels of each band will be used for each image to train the model. These bands can be consulted in Table 3.

On the other hand, the olive phenology states of each studied parcel are taken from the open data set, property of *Red de Alerta e Información Fitosanitaria* [17] belonging to *Junta de Andalucía*.

Table 3. Sentinel bands: description.

Band number	Band description	Wavelength range (nm)	Resolution (m)
B1	Coastal aerosol	433–453	60
B2	Blue	458–523	10
B3	Green	543–578	10
B4	Red	650–680	10
B5	Red-edge 1	698–713	20
B6	Red-edge 2	733–748	20
B7	Red-edge	773–793	20
B8	Near infrared (NIR)	785–900	10
B8A	Near infrared narrow (NIRn)	855–875	20
B9	Water vapour	935–955	60
B10	Shortwave infrared/Cirus	1360–1390	60
B11	Shortwave infrared 1 (SWIR1)	1565–1655	20
B12	Shortwave infrared 2 (SWIR 2)	2100–2280	20

Fourteen phenology states are detected in olive. In this work, they have been summarized in four: The state 1 which includes winter bud and moved bud states (2.25% of samples); state 2 with inflorescence, corolla flowering and petal drop states (29% of samples); state 3 which includes set fruit and hardening of the olive stone (65.13% of samples) and finally, state 4 than collected the veraison and matured fruit states (3.62% of samples).

This phenology dataset has been obtained from sixteen parcels for four regions of Andalucía (four for each one) as it can be observed in Fig. 1, with different characteristics between them, like variety, altitude, type of crop (traditional, intensive or super-intensive), etc. The characteristics of these parcels are shown in Table 2, where the altitude is expressed in meters, the surface in hectares the slope in % and the density in plants/hectares.

4.2 Evaluation Metric

In order to quantify the effectiveness of the methodology proposed, Accuracy was computed.

The metric used for Accuracy calculates the mean accuracy rate across all predictions for multi-class classification problems. The formula is:

$$Accuracy = \frac{1}{N} \sum_{k=1}^{|G|} \sum_{x:g(x)=k} I(g(x) = \hat{g}(x)) \tag{1}$$

where I is the indicator function, which returns 1 if the classes match and 0 otherwise.

Fig. 1. Localization of the parcels used for the study of transfer learning (Andalusia, Spain).

4.3 Experimental Settings

In order to set up the neural network for the experimentation carried out, the experimental settings established were the presented in Table 4.

Table 4. Experimental settings.

Parameter	Description
Batch size	With a value of 128, it defines the number of samples that will be propagated through the network
Epochs	One epoch is when an entire dataset is passed forward and backward through the neural network only once. The number of epochs used was 50
Optimizer	The optimizer used was *adam*. This optimizer recommends to leave the parameters at their default values
Hierarchical clustering	The method used to calculate the matrix distance was $ward.D2$ with its default values

4.4 Results and Discussion

The results obtained after applying the methodology to the four validation schemes described in the previous section are shown now.

Previously, the parcels have been clustered in the manner explained in the previous section. The dendrogram can be seen in Fig. 2.

Three clusters have been obtained. From now on, Cluster 1 will be made up of parcels P05, P04, P15, P13, P10, P14; Cluster 2 parcels P01, P03, P12 and Cluster 3 will contain parcels P07, P02, P09, P16, P06, P08, P11. Details of the distances between plots can be found at Fig. 3.

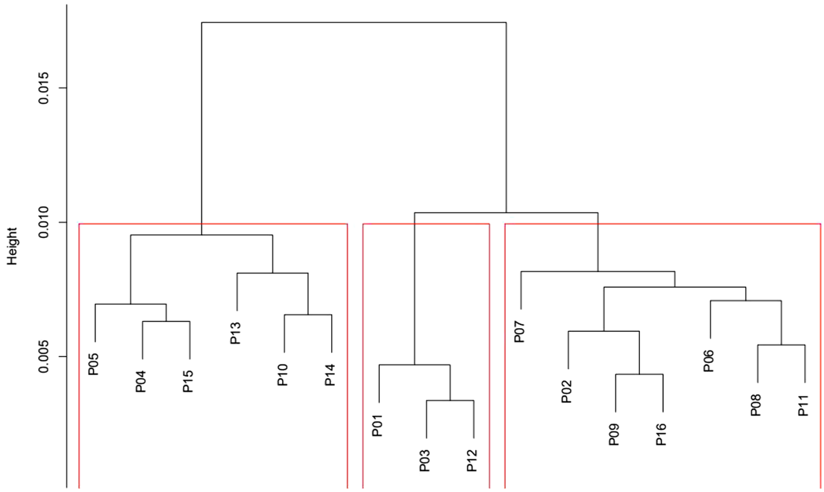

Fig. 2. Cluster dendrogram, with cutoff value leading to three parcel clusters.

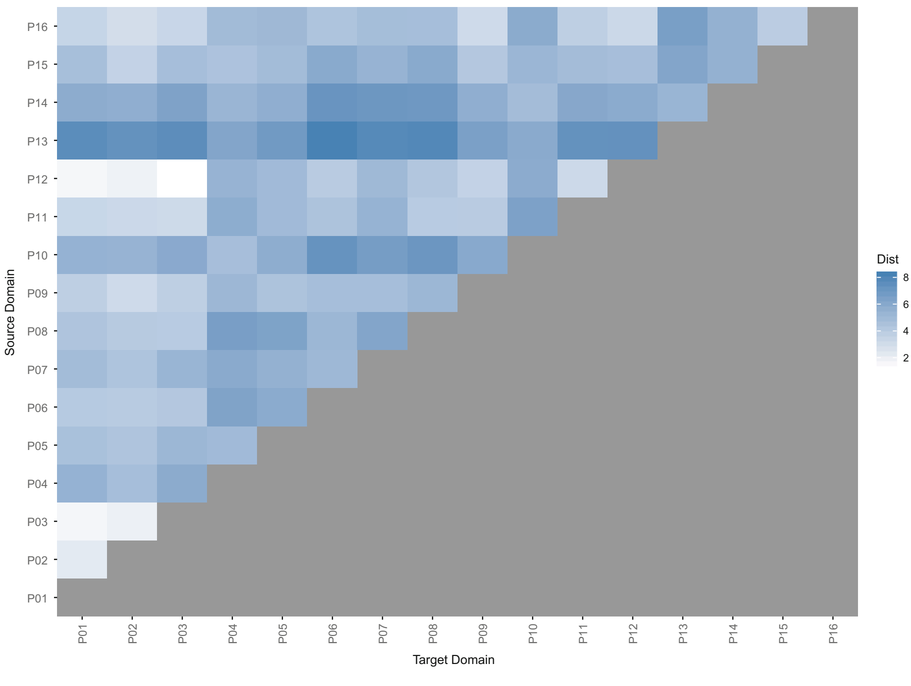

Fig. 3. Geographic distances among the parcels.

In this way, Cluster 2 and Cluster 3 are the most similar because they belong to the same branch. Cluster 1 has the most dissimilar information of the entire dataset.

Calculating the intra-cluster distance for the parcels, it can be observed that Cluster 1 distance is 1.49, Cluster 2 one is 5.42 and in the last one is 4.37. It can be observed that the parcels of Cluster 1 are most similar between them than the parcels of the other two clusters. This evidence is also reflected in Table 5.

Table 5. Average distance for parcels belonging to a same cluster.

Cluster	Intra-cluster distance
1	1.49
2	5.42
3	4.37

In Table 6, the accuracy of the four proposed schemes can be observed. The *Scheme* 1, where we train with the own parcel, throws an average accuracy of 80.67%. The improvement training with the parcels of the same cluster is 8.15%, being the improvements of 5.94% and 7.65% using the parcels of the others clusters.

In addition, it can be observed the improvements assuming the Scheme 1 as the baseline reference.

The improvement of some parcels is very significant using transfer learning techniques, as it can be observed in parcels number P03, P09, P11 and P13.

In order to analyze the results in more depth, the study will be separated by clusters, relating the improvements obtained to the distance between clusters and the number of parcels used for training.

Firstly, the study focuses on the parcels belonging to Cluster 1.

In this case, the *Scheme* 2.1 uses, for training, the parcels of its own cluster, the *Scheme* 2.2 uses the parcels of Cluster 2 and the *Scheme* 2.3 uses the parcels of Cluster 3.

The best average improvement is the one obtained in *Scheme* 2.1, using the parcels of its own cluster to apply transfer learning techniques. Very close, it is the improvement using Cluster 3. It can be explained because, although Cluster 3 is in another branch of the tree, and therefore, the distance between them is bigger, it is composed of many parcels, which provided a lot of general information that can be used to learn with these transfer learning techniques. The *Scheme* 2.2 throws less improvement since Cluster 2 provides less parcels and, also, it belongs to another branch of the tree.

In cases where parcels belong to Cluster 2, the *Scheme* 2.2 uses, for training, the parcels of its own cluster, the *Scheme* 2.2 uses the parcels of Cluster 3 and the *Scheme* 2.3 uses the parcels of Cluster 1.

Table 6. Accuracy for the proposed method for each phenology dataset and validated for Schemes 1, 2.1, 2.2 and 2.3. Cluster assignation for each parcel.

Parcels	Scheme 1	Scheme 2.1	Scheme 2.2	Scheme 2.3	Cluster
P01	86.68%	88.60%	90.90%	90.10%	2
P02	85.42%	90.80%	90.80%	90.80%	3
P03	82.22%	91.10%	91.10%	90.99%	2
P04	82.93%	86.31%	82.59%	87.10%	1
P05	83.84%	87.37%	85.49%	87.20%	1
P06	89.34%	89.63%	88.83%	88.63%	3
P07	90.12%	90.10%	90.80%	90.37%	3
P08	65.29%	71.15%	65.85%	67.13%	3
P09	76.08%	88.60%	85.44%	86.86%	3
P10	79.34%	84.01%	79.72%	88.04%	1
P11	81.49%	92.84%	92.07%	91.89%	3
P12	83.83%	85.37%	84.60%	84.71%	2
P13	27.08%	92.38%	81.35%	87.56%	1
P14	88.41%	91.70%	86.70%	91.70%	1
P15	95.43%	95.60%	94.05%	95.60%	1
P16	93.27%	95.60%	95.60%	94.41%	3
Average	80.67%	88.82%	86.62%	88.32%	–
Improvement	–	8.15%	5.94%	7.65%	–

The best average improvement is the one obtained in *Scheme* 2.2, using the parcels of Cluster 3 to apply transfer learning techniques. It can be explained because these two clusters are in the same branch of the tree and Cluster 3 contains many parcels which contribute with many general and similar information. *Scheme* 2.3, using Cluster 1 (with many parcels), has a big improvement but below the results of *Scheme* 2.2, most probably due to Cluster 1 is another branch of the tree. Finally, *Scheme* 2.1 is the worst of them, even training with the parcels of its own cluster. Although in this case, the distance intra-cluster is very small and the similarity between these parcels is great, the low number of parcels in this cluster affects the final results.

Finally, in cases where parcels belong to Cluster 3, the *Scheme* 2.1 uses, for training, the parcels of its own cluster, the *Scheme* 2.2 uses the parcels of Cluster 1 and the *Scheme* 2.3 uses the parcels of Cluster 2. The best average improvement is the obtained in *Scheme* 2.1, using the parcels of its own cluster to apply transfer -learning techniques. In second position it is the improvement using Cluster 2. It can be explained because, although Cluster 2 has a low number of clusters, these two clusters are in the same branch and the similarity between them is bigger. The *Scheme* 2.2 throws less improvement due to, although cluster

1 has many parcels, it belongs to another branch of the dendrogram and have less similarity among the rest of parcels.

5 Conclusions

In this paper the benefits of transfer learning have been empirically demonstrated using a dataset of phenological states of olive crops. Different experiments have been carried out to learn general knowledge from other image subsets. First, comparing the fourth validation schemes, the use of transfer learning techniques (Scheme 2.3) has provided a 7.65% of improvement with respect to different ways to train non-transfer learning models (Scheme 1, 2.1 and 2.2). Also, transfer learning has provided more robustness, reflected in the smaller standard deviations obtained, bringing more general knowledge of the treated data sets. According to the analysis of improvements, similarities of parcels, class imbalance ratios and a big number of instances, clear improvements have been observed. These works are a starting point to continue exploring the benefits of TL. As future works, the use of different architectures, the application of metaheuristics to determine optimal values for hyperparameters and the application of statistical tests to determine significance are proposed.

Acknowledgements. The authors would like to thank the Spanish Ministry of Economy and Competitiveness for the support under the project TIN2017-88209-C2-1-R.

References

1. Torres, J.F., Hadjout, D., Sebaa, A., Martínez-Álvarez, F., Troncoso, A.: Deep learning for time series forecasting: a survey. Big Data **9**, 3–21 (2021)
2. Lara-Benítez, P., Carranza-García, M., Riquelme, J.C.: An experimental review on deep learning architectures for time series forecasting. Int. J. Neural Syst. **31**(3), 2130001 (2021)
3. Deng, Z., Lu, J., Wu, D., Choi, K., Sun, S., Nojima, Y.: New advances in deep-transfer learning. IEEE Trans. Emerg. Top. Comput. Intell. **3**(5), 357–359 (2019)
4. Kim, D., Lim, W., Hong, M., Kim, H.: The structure of deep neural network for interpretable transfer learning. In: Proceedings of the IEEE International Conference on Big Data and Smart Computing, pp. 1–4 (2019)
5. Tan, C., Sun, F., Kong, T., Zhang, W., Yang, C., Liu, C.: A survey on deep transfer learning. In: Kůrková, V., Manolopoulos, Y., Hammer, B., Iliadis, L., Maglogiannis, I. (eds.) ICANN 2018. LNCS, vol. 11141, pp. 270–279. Springer, Cham (2018). https://doi.org/10.1007/978-3-030-01424-7_27
6. Liakos, K.G., Busato, P., Moshou, D., Pearson, S., Bochtis, D.: Machine learning in agriculture: a review. Sensors **18**(8), 2674 (2018)
7. Molina, M.Á., Asencio-Cortés, G., Riquelme, J.C., Martínez-Álvarez, F.: A preliminary study on deep transfer learning applied to image classification for small datasets. In: Herrero, Á., Cambra, C., Urda, D., Sedano, J., Quintián, H., Corchado, E. (eds.) SOCO 2020. AISC, vol. 1268, pp. 741–750. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-57802-2_71

8. Yang, Q., Shi, L., Han, J., Yu, J., Huang, K.: A near real-time deep learning approach for detecting rice phenology based on UAV images. Agric. For. Meteorol. **287**, 107938 (2020)
9. Hao, P., Di, L., Zhang, C., Guo, L.: Transfer learning for crop classification with cropland data layer data (CDL) as training samples. Sci. Total Environ. **733**, 138869 (2020)
10. Chen, J., Chen, J., Zhang, D., Sun, Y., Nanehkaran, Y.A.: Using deep transfer learning for image-based plant disease identification. Comput. Electron. Agric. **173**, 105393 (2020)
11. Wang, Z., Dai, Z., Póczos, B., Carbonell, J.: Characterizing and avoiding negative transfer. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 11293–11302 (2019)
12. Zhuang, F., et al.: A comprehensive survey on transfer learning. Proc. IEEE **109**(1), 43–76 (2020)
13. Xie, M., Jean, N., Burke, M., Lobell, D., Ermon, S.: Transfer learning from deep features for remote sensing and poverty mapping. In: Proceedings of the AAAI Conference on Artificial Intelligence, pp. 3929–3935 (2016)
14. Pires de Lima, R., Marfurt, K.: Convolutional neural network for remote-sensing scene classification: transfer learning analysis. Remote Sens. **12**(1), 86 (2020)
15. Abanda, A., Mori, U., Lozano, J.A.: A review on distance based time series classification. Data Min. Knowl. Disc. **33**(2), 378–412 (2018). https://doi.org/10.1007/s10618-018-0596-4
16. Chollet, F., et al.: Keras (2015). https://github.com/fchollet/keras
17. Junta de Andalucía: RAIF website of the Consejeria de Agricultura, pesca y desarrollo rural (2020). https://www.juntadeandalucia.es/agriculturapescaydesarrollorural/raif. Accessed 26 Mar 2020