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Apple scab detection using CNN and Transfer Learning

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Abstract. The goal of smart and precise horticulture is to increase yield and product quality by simultaneous reduction of pesticide application, thereby promoting the improvement of food security. The scope of this research is apple scab detection in the early stage of development using mobile phones and artificial intelligence based on convolutional neural network (CNN) applications. The research considers data acquisition and CNN training. Two datasets were collected - with images of scab infected fruits and leaves of an apple tree. However, data acquisition is a time-consuming process and scab appearance has a probability factor. Therefore, transfer learning is an appropriate training methodology. The goal of this research was to select the most suitable dataset for transfer learning for the apple scab detection domain and to evaluate the transfer learning impact comparing it with learning from scratch. The statistical analysis confirmed the positive effect of transfer learning on CNN performance with significance level 0.05.

Key words: agriculture, artificial intelligence, deep learning, fungus, machine learning, Malus, pathogen, precise horticulture, Venturia.

INTRODUCTION

Fruit growing has high profitability and potential for growth to provide the market with diverse local foods, and it occupies an important niche in the overall structure of agriculture. Apples are among the most widely grown and economically important fruit species worldwide and in Baltics (Kaufmane et al., 2017). In turn, scab disease caused by the ascomycetous fungi *Venturia inaequalis* (Cooke) G. Winter is economically the most important disease worldwide for apples (Tiirmaa et al., 2006; Belete & Boyraz, 2017). Currently, scab control heavily relies on fungicide applications. Due to environmental and food safety concerns, high adaptation ability of pathogens to applied fungicides as well as cost-effectiveness requirements, the need for changes in growing strategies have been highlighted during the last decade by apple scab research community and society. In cases where the use of pesticides can not be avoided, their applications should be more precise, more targeted and reduced substantially. One way to solve it is smart farming and precision horticulture that can greatly increase the effectiveness of pesticide applications and use them more selectively. In practice, smart farming and precision horticulture typically rely heavily on new technologies and digitalization, including early identification of diseases by image acquisition, recognition and severity analysis (Pujari et al., 2015).

With a goal to develop CNN model for embedded devices, which is possible to recognize apple scab in the early stage, our project group collected two datasets of images with a detected apple scab. Both datasets are accessible in *Kaggle* repository under *CC BY-NC-ND 4.0* license: *AppleScabFDs* (Web, 2021a) and *AppleScabLDs* (Web, 2021b). However, the collected datasets are imbalanced and are not sufficiently large. Meanwhile, CNN accuracy strongly depends on the size and quality of datasets (Soekhoe et al., 2016). One approach to overcome this problem is to use transfer learning. The learning techniques, which can learn from small datasets, are formally called few-shot learning (FSL). And there is a variety of FSL learning approaches that can be organized into four main categories: metalearning, metric learning, data augmentation, and transfer learning (Afifi et al., 2020). According to Weiss et al. (2016): 'The subject of transfer learning is a well-researched area as evidenced by more than 700 academic papers addressing the topic in the last 5 years'. Analyzing transfer learning impact using *ImageNet* datasets, Kornblith et al. (2019) found that, when networks are used as fixed feature extractors or fine-tuned, there is a strong correlation between *ImageNet* accuracy and transfer accuracy ($r = 0.99$ and 0.96, respectively). However, Ngiam et al. (2018) identify other important features for transfer learning - it is the usage of close categories. Cui et al. (2018) mention about the importance of domain similarity too and propose the methodology, which can be applied to measure a distance between datasets.

Generalizing, it is important to select an appropriate transfer learning dataset to train CNN for apple scab detection based on the collected *AppleScabFDs* and *AppleScabLDs* datasets. The methodology of Cui et al. (2018) can be applied for this task. However, according to the Cui et al. (2018), this methodology does not guarantee the optimal selection of the dataset for transfer learning, but they experimentally prove that this simple strategy works well in practice using different architectures of neural networks. Therefore, the accuracy of CNN model still must be tested. For example, *AlexNet* architecture can be applied as a benchmark to measure dataset similarity that will be additionally interesting, because it is a tradition to compare accuracy results using this architecture among deep learning scholars. Meanwhile, a feature extractor pretrained on *ImageNet* can be applied for measurement of domain similarity, as it is de-facto standard dataset for machine learning. However, it must be removed from source datasets for experiment clearance to avoid some possible feature extractor preferences.

The **goal** of our research is to select the most suitable dataset for transfer learning for the apple scab detection domain and to evaluate the transfer learning impact comparing it with learning from scratch.

The **objectives** of research:

– to collect the natural images of apple scab;
– to measure domain distance among datasets;
– to evaluate transfer learning impact on CNN accuracy.

The analysis of training results showed that transfer learning positively impacts CNN performance. The difference among the neural network models was statistically confirmed by Mann-Whitney-Wilcoxon test with significance level 0.05. *iFood251X* provided the best accuracy improvement compared with another datasets applied in the experiment: *CIFAR-10*, *CIFAR-100* and *PlantVillage*.

LITERATURE REVIEW

Lately, plant pathogen detection is a topical theme of research direction related to convolutional neural network (CNN) application in smart farming and horticulture. There can be mentioned that many modern researches, which are completed under smart farming trend, traditionally they are directed to develop a solution to identify specific pathogens of some plant or based on open datasets like *PlantVillage*. For example, Adhikari et al. (2018), Rangarajan et al. (2018) and Salih et al. (2020) presented solutions for tomato disease detection, which were based on CNN application. Meanwhile, Afifi et al. (2021) and Esgario et al. (2020) used deep learning for coffee pathogen detection, but Muhammad et al. (2021) - for disease of *Aloe vera*.

Describing the detection of apple pathogens, Liu et al. (2018) applied *AlexNet* for detection of following apple pathogens: mosaic virus, brown spot, rust and *Alternaria* leaf spot. Baranwal et al. (2019) applied augmentation and *LeNet-5* architecture design for apple subgroup classification extracted from *PlantVillage* dataset.

Considering the object of research - transfer learning, the related experiments, when transfer learning was applied for apple scab detection, were already completed. For example, Yan et al. (2020) and Khan et al. (2020) experimented with *VGG and AlexNet* architectures pretrained on *ImageNet*. May be Afifi et al. (2021) experiments are not directly related to apple scab monitoring, but they provide comprehensive study of FSL techniques based on *PlantVillage* dataset.

Touching on the topic of embedded devices. Petrellis, N. (2017) provided review of existing solutions, as well as, proposed own mobile application based on spectral analysis. However, Picon et al. (2019) proposed early identification application of three relevant European endemic wheat diseases.

Other active research direction is IoT application in the food industry. For example, Nasir et al. (2020) and Xenakis et al. (2020) proposed CNN solutions for IoT to detect plant diseases.

The current limitations of deep learning related to plant disease diagnostic are discussed in review of Arsenovic et al. (2019), where authors mention the limitation that currently available datasets do not contain images gathered and labeled from real-life situations. A more wide review of challenges is provided by Hasan et al. (2020), who underline the importance of new datasets with natural images and CNN solutions with smaller computation time for embedded solutions. That depicts the importance and **originality** of the current research, which considered dataset collection with natural images to develop an embedded CNN solution for mobile applications.

MATERIALS AND METHODS

The collection of digital images were carried out in different locations of Latvia (Fig. 1). Digital images with characteristic scab symptoms on leaves and fruits were collected from the Institute of Horticulture (LatHort) apple collection (Krimūnu parish, Dobeles district, two locations: 56.612338, 23.305949; 56.610936, 23.298447), commercial orchard (Skaistkalnes parish, Vecumnieku district 56.3652416, 24.6025912), and home gardens (Valgundes parish: 56.695785, 23.718894; Ozolnieku parish: 56.684399, 23.834508; Sējas parish: 57.285628, 24.479879). Data collection was done during the apple growing season, from the beginning of June 2020, when the first signs of apple scab infection began to appear on the leaves, until the end of September 2020, when both leaves and fruits showed other signs of damage preventing distinguishing from apple scab and were at the end of the growing season.

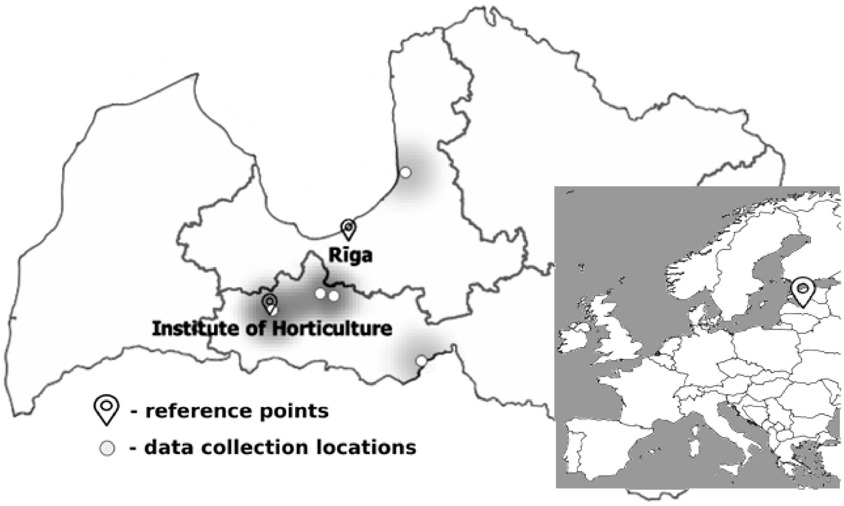

Figure 1. Locations of image acquisition for datasets *AppleScabDLs* and *AppleScabDFs*.

The collection of digital images was carried out using two types of devices with different camera resolutions - smartphone cameras (12 MP, 13 MP, 48 MP) and a digital compact camera (10 MP).

Apple leaves and fruits were photographed at different development stages and with different signs of damage.

The collection of images was carried out in field conditions, in orchards. Apple leaves and fruits were photographed as separate objects. The images were taken at three different stages of the day - in the morning (9:00–10:00), around noon (12:00–14:00), as well as in the evening (16:00–17:00) to provide a variety of natural light conditions. The images were also taken on both sunny days and overcast days to provide different types of light (soft light and hard light).

The leaves and fruits were framed so that they occupied the image area as much as possible and were in the center of the image, and the focal point was on the object. The object may have had other leaves or fruits in the background. The same object was photographed from multiple viewpoints.

For each subject, leaf or fruits, the signs of apple scab expression caused by *V. inaequalis* had been documented by imaging. Images of apple leaves and fruits without visual damage and with visual noise like drops of water, insects, shadows, mechanical or biological damage were obtained in parallel with sick leaves and fruits.

The resulting images were manually reviewed and grouped into two datasets called *AppleScabFDs* (images with apple fruits) and *AppleScabLDs* (images with apple leaves). Where in turn the images of leaves and fruits were grouped into two data subsets - images with scab symptoms and images without scab symptoms. The examples of dataset photos are provided in Fig. 2.

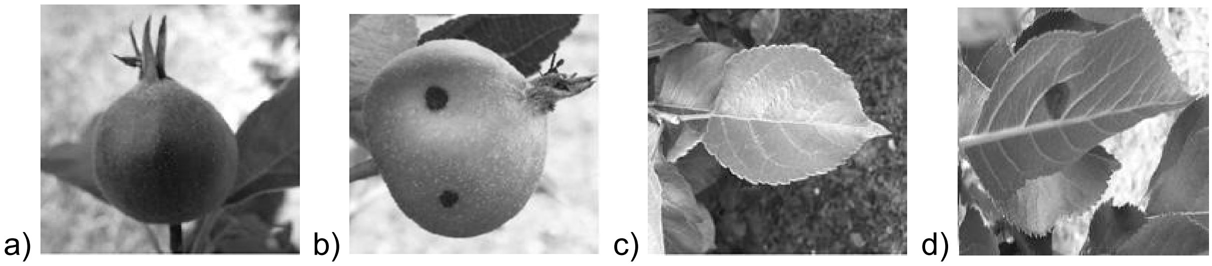

Figure 2. Photo examples from collected datasets: a) healthy apple fruit; b) apple fruit infected by scab; c) healthy apple leaf; d) leaf infected by apple scab.

The experiment consists of five stages (the activity diagram of the experiment is provided in Fig. 3):

1) Measurement of distance between image datasets is completed considering the methodology described in the scientific article of Cui et al. (2018).

2) *AlexNet* model is trained using transfer learning methodology, where the fine-tuning approach is applied for retraining CNN with a new dataset.

3) Investigation of CNN accuracy is completed. Training accuracy, validation accuracy and Cohen Kappa are measured.

4) Statistical analysis were performed to identify transfer learning impact neural network accuracy.

5) The relationship between EMD and obtained accuracy is analyzed using line diagrams.

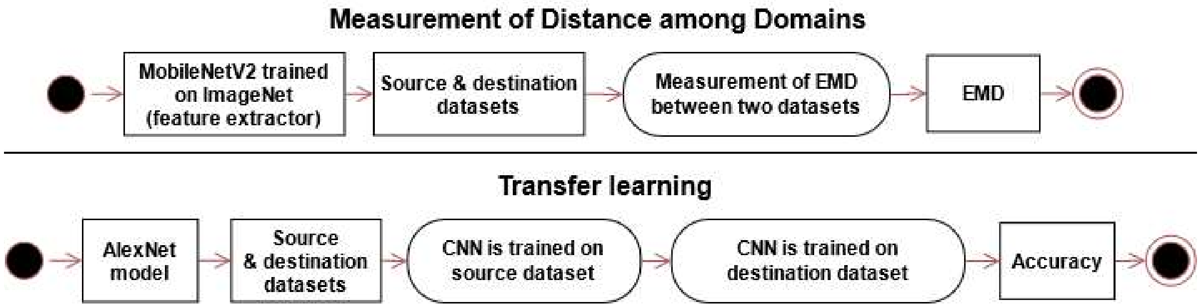

Figure 3. Activity diagram of experiment.

Cui et al. (2018) methodology is based on Earth Mover's Distance and feature extractor application, for example, CNN trained on a large dataset like *ImageNet*.

If S is the source dataset, but T – the target dataset, then each category can be represented as $S = \{(s_i, w_i)\}_{i=1}^{m}$ and $T = \{(t_j, w_j)\}_{j=1}^{n}$, where s_i is the i-th category of dataset S, but weight w_i are normalized numbers of images in datasets (1):

$$\sum w_i = \sum w_j = 1. \qquad (1)$$

Using feature extractor, each image can be transformed into feature vectors $g(s_i)$ and $g(t_j)$ respectively. To calculate the distance between two categories, the mean vectors of each category is applied (2):

$$d_{i,j} = \left\| \bar{g}(s_i) - \bar{g}(t_j) \right\|. \quad (2)$$

Cui et al. (2018) propose Euclidean metric to calculate distance $d_{i,j}$ as the cost of flow from category i to j. Then linear programming algorithms are applied to search optimal flow $f_{i,j}$. In results, the Earth Mover's Distance is calculated using Eq. 3:

$$d(S,T) = EMD(S,T) = \frac{\sum_{i=1,j=1}^{m,n} f_{i,j} \cdot d_{i,j}}{\sum_{i=1,j=1}^{m,n} f_{i,j}}. \quad (3)$$

Considering domain similarity, Cui et al. (2018) propose next equition (4):

$$sim(S,T) = e^{-\gamma \cdot d(S,T)}, \quad (4)$$

where the coefficient $\gamma = 0.001$.

Python 3.6, *Keras* and *Jupyter Notebook* were applied to write scripts for experiments to measure Earth Mover's distances between datasets and to train convolutional neural networks. The experiment was completed using computers equipped with *NVIDIA GTX 1050* and *RTX 2070*.

Three destination datasets are investigated in the experiment: two our datasets (*AppleScabFDs* and *AppleScabLDs*) and *Fruits360* dataset with 3 categories ('apples', 'pears' and 'others'), which will be abbreviated as *Fruits360-3*. *Fruits360-3* dataset is selected due to our previous experiment (Kodors et al., 2020). This data provides the possibility to compare the previous results of learning from scratch with the results of transfer learning. Next, five source datasets were selected for transfer learning: *Fruits-360* (Mureşan & Oltean, 2018), *CIFAR-10* (Krizhevsky, 2009), *CIFAR-100* (Krizhevsky, 2009), *iFood251X* (Kaur et al., 2019) and *PlantVillage* (Hughes & Salathé, 2015). Some examples of images are provided in Fig. 4 to make a more intuitive understanding of the dataset content.

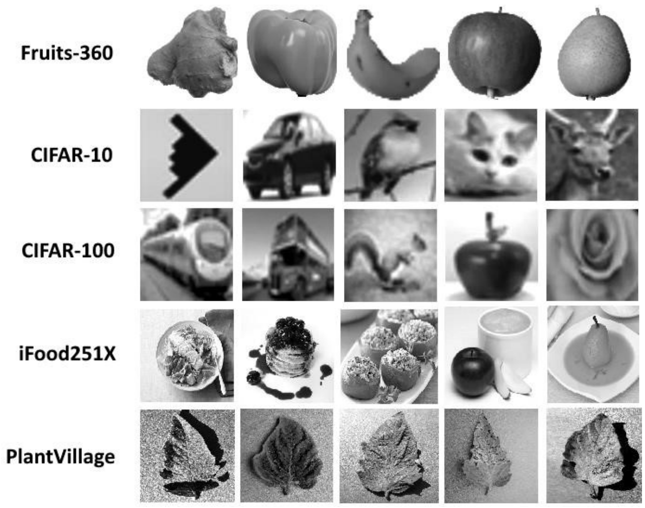

Figure 4. Image examples of datasets.

The domain similarity was calculated by the Earth Mover's distance (EMD) and the method described in the article of Cui et al. (2018) measuring EMD using *MobileNetV2* CNN trained on *ImageNet* dataset as a feature extractor. Therefore, *ImageNet* is not included in the comparison, because it is applied by the feature extractor - as benchmark.

AlexNet architecture is a benchmark to compare deep learning results. Additionally, *AlexNet* architecture was selected due to its weak classification results in our previous experiment (Kodors et al., 2020). Therefore, the transfer learning impact can be more easily detected. The *AlexNet* model of previous research (Kodors et al., 2020) is applied in the experiment to obtain comparable data (Fig. 5).

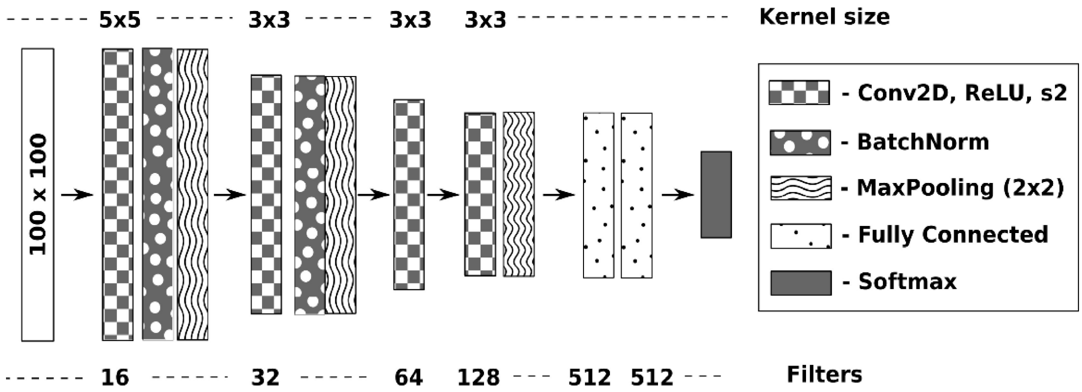

Figure 5. Structure of *AlexNet* model applied in the experiment.

The Mann-Whitney-Wilcoxon test with significance level 0.05 is applied to identify differences among the models trained on *Fruits360-3*, obtained during this experiment and in the previous our experiment (Kodors et al., 2020). The relationship between EMD and the obtained neural network accuracy, as well as, the most appropriate dataset for pretraining are analyzed using line diagrams constructed by the approach presented in the article of Cui et al. (2018).

RESULTS AND DISCUSSION

Two datasets with images of apple scab symptoms were collected (Fig. 2). One dataset contains examples of scab symptoms on leaves, another - on apple fruits. From the perspective of artificial intelligence engineering, it must be mentioned that both datasets are imbalanced (see Fig. 6), because it strongly impacts CNN training results.

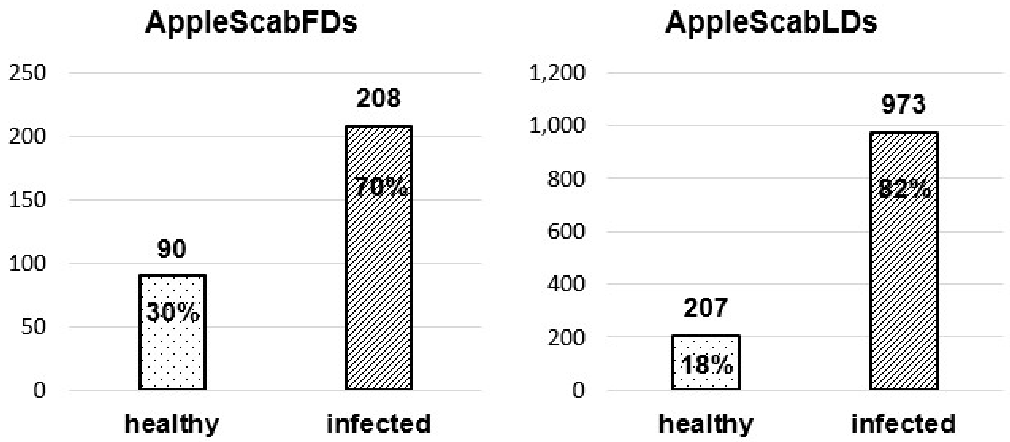

Figure 6. Proportion of the number of cases in different classes.

All calculated EMDs across the domains are presented in Table 1. *iFood251X* dataset showed the closest EMDs to all destination datasets of experiment. Meanwhile, *CIFAR10* is the furthest from the collected scab datasets, *AppleScabFDs* and *AppleScabLDs*. It must be noted that *CIFAR10* and *CIFAR100* have simple content images including apples and pears, but *PlantVillage* has images of healthy and infected leaves, however, they are not natural images and photographed in laboratory conditions.

At the same time, *iFood251X* contains natural images with complex content. Therefore, the closeness of *iFood251X* can be explained by the wealth of feature vocabulary. It means that datasets with inatural images are not effective for CNN pretraining, which will analyze natural images.

Table 1. Earth mover's distance between datasets

Datasets		Destination		
		Fruits360-3	*AppleScabFDs*	*AppleScabLDs*
Source	*CIFAR10*	0.79308	0.80581	0.79781
	CIFAR100	0.80161	0.81133	0.80229
	iFood251X [1]	0.80865	0.85017	0.83711
	PlantVillage	0.78553	0.82449	0.83655

[1] Source dataset, which is the closest to all destination datasets.

The Mann-Whitney-Wilcoxon test was completed to identify statistically reliable differences between training from scratch and transfer learning. *Fruits360-3* dataset was selected for comparison. The calculated probability values (*p*-values) are provided in Table 2.

Table 2. Results of Mann-Whitney-Wilcoxon test (*p*-values)

From Scratch	*Internal TL*	*CIFAR10*	*CIFAR100*	*iFood251X*	*PlantVillage*
1.00000	0.00912	0.00221	0.00221	0.00221	0.00459

However, average accuracies are depicted in the box diagram (see Fig. 7). Thus, it is important to mention that internal transfer learning provided performance improvement, when CNN was initially trained on the original *Fruits360* dataset with 120 classes and then retrained on the same dataset with 3 classes (*Fruits360-3*). These results agree with Ngiam, et al. (2018) conclusions that features learned on coarse-grained classes do not provide significant benefits transferred to fine-grained datasets, but transfer learning using close categories is preferable than usage of entire dataset (Barman et al., 2019). At the same time, *CIFAR* and *iFood251X* provided significant improvements. However, *CIFAR-100* dataset was better than *iFood251X* despite the higher EMD. According to Ngiam et al. (2018), transfer learning using close categories is preferable than usage of the entire dataset that can explain better results of CIFAR-100, because it contains apple and pear images. Meanwhile, *PlantVillage* provided the smallest EMD and decreased CNN accuracy. Authors of EMD method mention that this greedy way of selection has no guarantee on the optimality of the selected subset in terms of domain similarity, but this simple

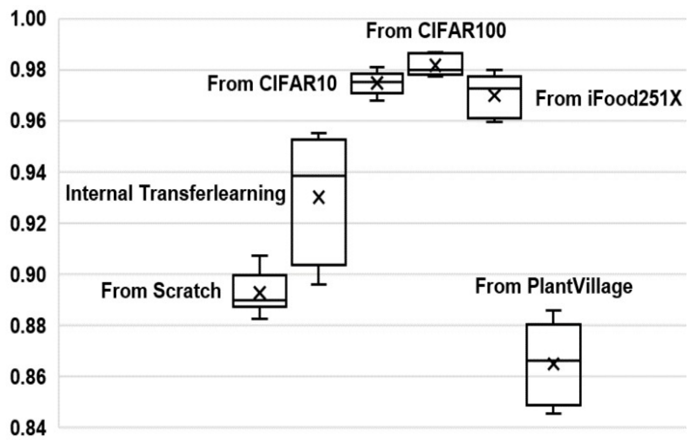

Figure 7. *Fruits360-3* trained using different approaches.

strategy works well in practice (Cui et al., 2018). Therefore, maybe it does not guarantee the optimality of the selected subset, but it can be an effective method to choose datasets for experiments with transfer learning.

The constructed line diagrams (Figs 8–10), which depict the relationship between EMD and neural network accuracy, showed that performance of the models trained on balanced dataset *Fruits360-3* was improved using transfer learning. These results coincide with the investigations of Cui et al. (2018). However, imbalanced datasets, *AppleScabFDs* and *AppleScabLDs*, must be analysed independently, because they provide other shapes of performance lines.

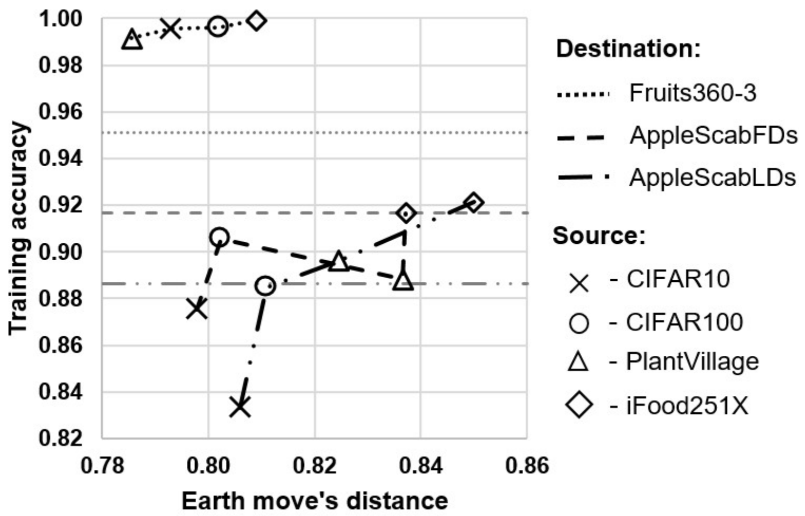

Figure 8. Relationship among EMD, transfer learning and training accuracy: horizontal lines - from scratch.

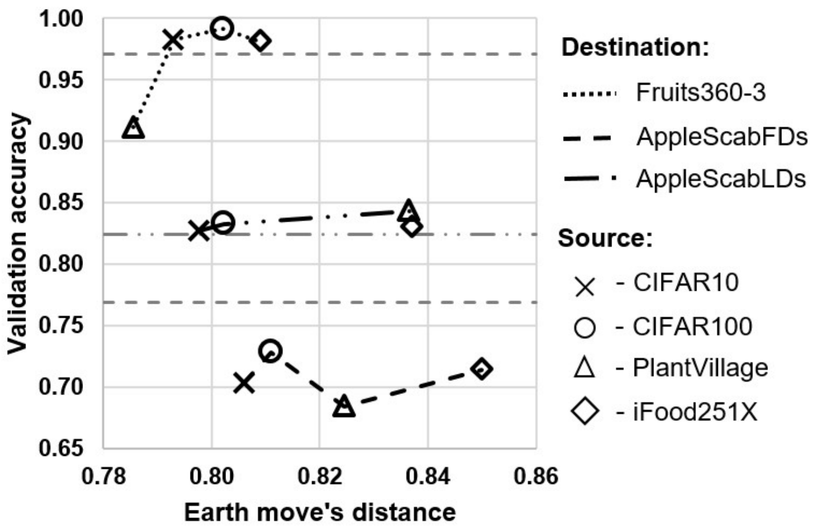

Figure 9. Relationship among EMD, transfer learning and validation accuracy: horizontal lines - from scratch.

AppleScabFDs and *AppleScabLDs* datasets obtained different performance results among themselves. Based on Cohen Kappa analysis and comparing it with training from scratch (see Fig. 10), transfer learning provided a stronger impact on the smallest dataset - *AppleScabFDs* (see Fig. 5), it can be explained by Weiss et al., 2016, and Barman et al., 2019, investigations, that transfer learning provides a strong positive impact on small dataset. It must be mentioned, that the performance lines are like the trends of lines provided in the article of Cui et al. (2018). Meanwhile, the systematic study of Buda et al. (2018) showed that the effect of class imbalance on classification performance is detrimental and recommend the application of oversampling to solve a problem with imbalanced datasets. However, Wang et al. (2014) showed that oversampling can call overfitting. *AppleScabLDs* is strongly imbalanced and large, therefore it provides such a dramatic effect on transfer learning comparing with training from scratch.

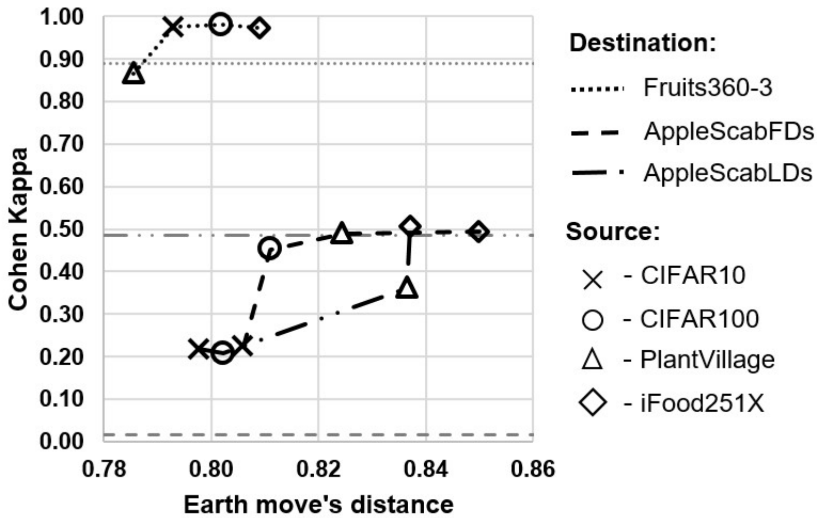

Figure 10. Relationship among EMD, transfer learning and Cohen Kappa: horizontal lines - from scratch.

CIFAR100 sufficiently well improved the classification accuracy for *Fruits360-3* dataset comparing with the closest dataset - *iFood251X* (see Table 1 and Figs 7–10), because they contained similar images. For the same reason, *PlantVillage* improved recognition accuracy for *AppleScabLDs* (see Figs 9–10). These results provide the similar conclusion to Huh et al. (2016) - subclasses which share a common visual structure allow the CNN to learn features that are more generalizable.

CONCLUSIONS

The resulting images were manually reviewed and grouped into two datasets called *AppleScabFDs* (images with apple fruits) and *AppleScabLDs* (images with apple leaves). Where in turn the images of leaves and fruits were grouped into two data subsets - images with scab symptoms and images without scab symptoms. Collected datasets are accessible in *Kaggle* repository (Web, 2021a, 2001b). It should be mentioned that both datasets are imbalanced (Fig. 6), that prevents CNN to get high accuracy.

The experiment showed that transfer learning positively affects CNN accuracy. However, it is important to measure Earth Mover’s distance selecting dataset for pretraining, since an inappropriate dataset can otherwise provide a negative effect. Additionally, it is important to select datasets with similar categories considering data collection and usage principles. Therefore, if there are plans for the use of neural networks in natural conditions, source datasets must be collected in natural conditions too. As well as, the size of the dataset plays an essential role: transfer learning strongly improves the results of small imbalanced dataset, but a large imbalanced dataset is slowly compensated by transfer learning and may be the training from scratch is more effective for it.

Obtained results showed that the most important task for further data collection is to improve the datasets, *AppleScabFDs* and *AppleScabLDs*, by collecting more photos for minimal classes. The dataset should be more balanced and the image acquisition process should be monitored in a way to collect an equal number of images of all classes, since the plant disease experts are more concentrated during data collection on anomalies and manifestations of diseases than intact parts of plants. Comparing the results with related researches, it can be concluded: if the problem with imbalanced data is solved, the application accuracy will be obtained.

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