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OVERVIEW OF THE USE OF CONVOLUTIONAL NEURAL NETWORKS IN PLANT DISEASE RECOGNITION BASED ON THE LEAF IMAGE

Perišić B. Natalija, Jovanović Ž. Radiša, Vesović V. Mitra, Sretenović Dobrić A. Aleksandra

University of Belgrade, Faculty of Mechanical Engineering, Belgrade, Serbia

Abstract. *The use of artificial intelligence in modern agriculture is on the rise, due to the fact that it provides a possibility for more efficient production, better decision making and reduction of the costs. This research takes into consideration the use of the convolutional neural networks for diagnosing plant illnesses based on the leaf image. Detection of plant diseases in the early phase can improve the quality of the food products and minimize the loses. Convolutional neural networks are a type of deep learning method that is one of the most used models for solving image recognition, classification and detection tasks. Therefore, it is justified to anticipate that they can be very effectively applied in the agriculture sector. This paper covers plant species that are the most significant for Serbian production. Various models have been presented and analyzed, while highlighting their advantages and disadvantages when applied for solving this task.*

Key words: *Convolutional neural networks, plant disease recognition, artificial intelligence*

1. INTRODUCTION

Today, agriculture faces various challenges as it is necessary to increase food production in sustainable manner due to the expansion of global population while using limited resources such as water and land [1]. Traditional agriculture methods are not capable of coping with the posed demands for few reasons. Firstly, it does not ensure efficient use of resources like water, fertilizer, pesticides and insecticides which may cause harm to the environment and health of the living beings. Secondly, a lack of information and analytics about crop conditions can be noticed, which complicates the decision-making process. Thirdly, traditional agriculture requires a large amount of physical work which is exhausting and expensive. Finally, it relies on subjective assessment during visual examination of field which may result in late detection of crop diseases. In order to overcome the mentioned disadvantages, the idea of applying new technologies in agriculture, known as Agriculture 4.0, appeared and it is constantly developing and improving. The mission of agriculture 4.0 is upgrading agriculture strategies and methods to create optimized value chain by utilizing a wide range of modern technologies that enhance processes at all stages of agricultural production chain [2]. Also, the solutions of the fourth agricultural revolution tend to be eco-friendly and efficient in satisfying requirements of society and consumers [3]. Technologies such as GPS, satellite imaging, sensors and different software enable precise agriculture which refers to optimal management of the resources using chemical means only when it is necessary and in prescribed doses or adequate utilization of agricultural land. In order to obtain all indispensable information that facilitate decision-making process agriculture 4.0 uses Internet of Things, Big Data and sensors. The amount of human hard physical work is reduced by implementing automatization techniques, robotic and artificial intelligence, while efficiency is improved, at the same time. Agriculture 4.0 allows continuous monitoring of crops by combining outputs from sensors, drones, cameras and methods of artificial intelligence which leads to faster detection and solving problems.

When it comes to the monitoring of fields, one of the most important tasks is recognition of plant diseases in the early phase. If disease is diagnosed early, then certain steps can be taken to suppress the illness before it spreads on the whole crop, thus preventing yield loss and preserving product quality. One of the benefits is also saving resources because they are used only on infected areas, which means minimizing consumption of chemicals, time and money. In addition, pollution can be significantly reduced which contributes to the preservation of the environment.

Convolutional Neural Network (CNN) is one of the mostly used methods for detecting plant diseases. It is a type of a deep neural network that is highly efficient in solving computer vision tasks. The main reason that explains this fact is their ability to achieve excellent performance without manual extraction of important features from input data.

This research considers the use of the CNN for disease recognition based on the leaf image for plants that are the most common on the crops in Serbia. This paper is organized in several parts – after introduction, applied methodology for the study is described in the second section, following with the basic information about CNN. The fourth section describes the selection of plants crops considered in the study. Results and discussion are presented in the fifth section, while the sixth section summarizes the derived conclusions.

2. METHODOLOGY

This paper is focused on finding the best possible solution for recognition of plant diseases, for plant species that are the most common in Serbian agriculture by using CNN. Therefore, the first step of the research is analyzing the representation of plant species on crops in Serbia. The second step is finding research papers dealing with the application of CNN for disease recognition, based on the leaf image for plants that bring the highest yield in Serbia. Final, third step is to choose two species that are the most significant for Serbian plant growers, while considering that those species are also frequently analyzed in scientific research. The Scopus database is used in the second step. The main comparison criteria are CNN model's accuracy and number of diseases that can be recognized by the CNN models. Accuracy is the performance evaluation parameter that shows the percentage of correctly classified samples among all samples.

3. CONVOLUTIONAL NEURAL NETWORKS

CNNs represent type of deep learning networks that are often used for solving computer vision tasks such as image classification, object recognition, recognition, etc. The architecture of CNN consists of three types of layers – convolutional, pooling and fully connected layer. In convolutional layer a filter made of weight coefficients that should be learned in the training process, slides among input image creating feature map. In pooling layer information from input feature map are reduced in order to lower computational costs and training time, transmitting the most important information to the next layer. The role of these two layers is feature extraction. The role of fully connected layer is making the final conclusion about input sample and generating network's output by applying weights to flatten output from the last pooling layer. They find their application in robotics [4], cybersecurity [5], etc. More information about CNNs can be found in [6].

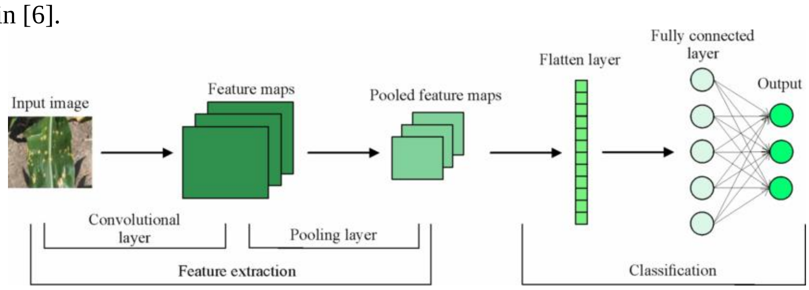

Fig. 1 General architecture of CNN

4. SELECTION OF PLANT SPECIES FOR THE OVERVIEW ANALYSIS

This section deals with the selection of plant species whose diseases recognition by CNNs will be discussed in this study. The selection is made in previously described steps.

4.1. Analysis of the significance of plant species in Serbia

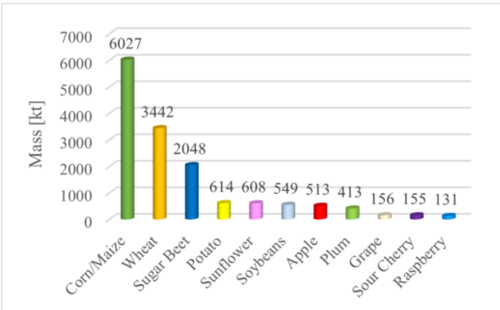

Fig. 2 Bar diagram of crop production in 2021

Data obtained by Statistical Office of the Republic of Serbia are used for plant significance analysis. As it is written in [7], there are given "*the main statistical data on the national social and economic development*", so it is considered that the mentioned plants are the most significant for Serbian economy and therefore, the most commonly grown on crops. Document [8] obtains information about achieved production of wheat and early fruit as well as expected production of late crops, fruits and grapes in 2021. By combining gathered information from [7] and [8] the top 10 yields come from plants: corn (maize), wheat, sugar beet, potato, sunflower, apple, plum, grape, sour cherry and raspberry. It is noticed that there is no data about achieved production of soybeans, while the predicted yield is very high, so soybean is considered as eleventh significant plant. Bar diagram of crop production in 2021 is shown in Fig. 2.

4.2. Representation of suitable plant species in scientific work

In order to investigate the frequency of research about diagnosing plant diseases by using CNNs for plants declared as the most significant for Serbian production, SCOPUS base is used. The name of the plant is entered in the search field together with words disease, leaf, and convolutional neural network. The percentage of found papers is shown in Fig. 3.

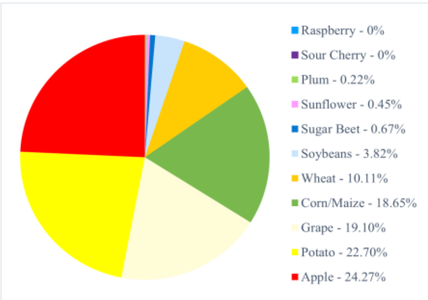

Fig. 3 Percentage of papers on plant diseases diagnosis using CNNs in SCOPUS database

4.3. Selection of plant species for further analysis

As it can be observed, amount of scientific research does not completely match the significance of plant species. There is just one paper that analyzes plum, and only few papers dealing with sugar beet, sunflower. Also, there is no papers that take in consideration raspberry and sour cherry. In further work, papers about diagnosing leaf diseases of wheat and corn using CNN will be analyzed as they have the most yield in Serbia. The second reason is that significant number of research papers about these plants can be found. The criterion for choosing papers is based on the number of citations and applied CNN models.

5. RESULTS AND DISCUSSION

5.1. Recognition of wheat leaf diseases using CNN

The best obtained results from papers about wheat diseases are presented in Table 1. Number of classes includes all classes of diseases and class of healthy leaves that CNN models are trained to recognize. Abbreviation ‘avg’ stands for average accuracy.

Table 1 Accuracies obtained by applying different CNN for recognition of wheat leaf diseases

Plant species	Reference	CNN architecture	Classes	Accuracy [%]
Wheat	[9]	Tairu	4	90.47
		AlexNet		94.04
		LeNet		97.61
	[10]	AlexNet	8	91.54
		LeNet-5		89.15
		Inception-V3		94.31
		ZFNet		92.79
		DACNN		95.18
	[11]	VGG-19	5	79.05
		ZFNet		86.32
		PNN		72.14
		GoogleNet		89.84
		Inception-V4		82.73
		EfficientNet-B7		87.96
		RFE-CNN		**99.95**
	[12]	AlexNet	8	72
		VGG-16		78
		M-bCNN-CKM-2		83
		M-bCNN-CKM-3		91
	[13]	VGG-16	10	97.88
		ResNet50		90.87
		Custom		81.96
	[14]	Custom	3	94.91
	[15]	VGG-16	4	85.25 (avg)
		Inception-V3		92 (avg)
		RenNet50		89.5 (avg)
		DenseNet121		91.5 (avg)
		EfficientNet-B6		88.5 (avg)
		ShuffleNet-V2		88.75 (avg)
		MobileNet-V3		88.5 (avg)
	[16]	Custom	2	93
	[17]	AlexNet	7	87.15
		VGG-16		87.44
		ResNet34		95.05
		ResNet50		96.52
		ResNet101		95.68
		InceptionResNet-V2		96.7
		MobileNet-V1		94.41
		MobileNet-V2		95.23
		MobileNet-V3_small		95.34
		MobileNet-V3_large		96.75
		EfficientNet-B0		96.81
		IRCE		98.76
	[18]	AlexNet	4	84.54

All mentioned models are trained to recognize certain leaf diseases of wheat, except for model in [16] which is trained to classify samples only in two classes – healthy and not healthy. Powdery mildew is the most common disease that can be recognized, as it has been mentioned in every paper other than [14] and [16], following the leaf rust that has not been mentioned only in [9], [14] and [16]. Stripe rust is one of the disease classes in [10], [12], [14], [15] and [18]. Septoria is included in [9], [11] and [14], while the recognition of the bacterial leaf blight can be found in [10] - [12]. Papers [10] and [12] take in consideration classes of mechanical damage, bacterial leaf streak and cochliobolus heterostrophus. Also, brown rust can be found in [9], wheat streak mosaic in [13], stem rust in [18] and tan spot in [13] and [17]. Papers [13] and [17] cover some diseases that are not strictly related to the leaf such as crown root rot, head blight and wheat loose smut, while the paper [13] include also Karnal bunt and black chaff. The highest accuracy of 99.95% is obtained in [11] by using network that included two parallel CNNs to extract the basic features of images, residual channel attention block for optimizing basic features, feedback block for training of those features and another CNN with elliptic metric learning to process and classify samples, named RFE-CNN. However, it should be pointed out that papers [10] and [12] offer models that can classify the highest number of leaf diseases and accuracy of 95.18% obtained by differential amplification CNN from [10] is significantly high. Only CNN from [18] is tested on images taken by mobile device from actual fields and it is stated that images were correctly classified, but other information cannot be found.

5.2. Recognition of maize leaf diseases using CNN

The results from the analyzed papers about detection of maize diseases are presented in Table 2. As previous, number of classes include healthy class as well.

All researches, except [28], offer solution for diagnosing common rust. Only authors in [27] do not include a class of northern leaf blight disease, while there is a type of disease named “big spot”, which is not precisely described. In every paper, with the exception of [19] and [28], exists the class of grey leaf spot disease. CNN architectures from [23] and [28] are trained to recognize curvularia leaf spot. Most classes can be found in [23], where southern leaf blight, brown spot, round spot and dwarf mosaic are included among previous mentioned classes of diseases. The highest accuracy of 99.84% is obtained by using EfficientNet-B0 in [21], while proposed optimized DenseNet achieved 98.06% accuracy, but it has the lowest number of parameters and the shortest training time, which can be significant in terms of real-time application. Study [23] developed improved GoogLeNet model that can classify eight types of diseases and healthy leaf with the accuracy of 98.9%. However, papers [19], [24] – [26] brought closer their models to real-time disease diagnosing usage. In [19] images are taken in real life conditions and sent via Wi-Fi system that uses proposed CNN to classify diseases, which is later displayed on LCD screen. The average accuracy obtained on real-life classification problems is 88.66%, which is high. In study [24] models are also trained under natural environment conditions and the highest accuracy is obtained by proposed TCI-ALEXN, 93.28%. Paper [25] used CNN with OpenMP implementation to achieve accuracy of 84%, which is shown in Table 2. Authors of [26] used ResNet as model with highest accuracy of all deep networks and MobileNet as model with highest accuracy of all lightweight models, on PlantVillage dataset, to train them on dataset collected by mobile device. ResNet achieve highest accuracy of 98.77%, while highest accuracy obtained by MobileNet is 99.11%.

Table 2 Accuracies obtained by applying different CNNs for the recognition of maize leaf diseases

Plant species	Reference	CNN architecture	Classes	Accuracy [%]
Maize	[19]	Custom	3	96.7
	[20]	LeNet	4	97.89
	[21]	EfficientNet-B0	4	**99.84**
		VGG-19		96.36
		XceptionNet		93.52
		NasNet		91.9
		DenseNet		98.06
	[22]	Custom	4	92.85
	[23]	Cifar10	9	98.8
		GoogLeNet		98.9
	[24]	VGG-16	4	89.98
		DenseNet		92.29
		ResNet50		92.84
		AlexNet		93.77
		TCI-ALEXN		99.18
	[25]	Custom	4	84%
	[26]	VGG-16	4	96.76
		VGG-19		97.04
		ResNet		99.48
		DenseNet121		97.47
		DenseNet169		97.67
		DenseNet201		97.99
		Inception-V3		98.82
		InceptionResNet-V2		99.31
		Xception		96.81
		MobileNet		98.69
		MobileNet-V2		98.04
		ShuffleNet		96.08
	[27]	AlexNet	4	No data
		VGG-19		93.33
		ResNet50		97.75
		2-chanel CNN		98.33
	[28]	AlexNet	3	82.74 (avg)
		GoogLeNet		86.29 (avg)
		ECNN		92.92 (avg)

5.3. Advantages and disadvantages of using CNN for diagnosing plant diseases based on leaf image

Application of CNNs for tasks of diagnosing diseases has great advantages, but also some limitations that the researchers are trying to overcome. CNN models bring benefit to the phytopathologist, because even though they can interpret plants conditions and diagnose diseases by themselves, it can help them to confirm their hypotheses and make decision quicker, especially in cases when the disease is not expanded on the whole field [9]. Also, it can help less experienced farmers to detect and diagnose diseases in order for them to take measures and actions for suppressing diseases immediately [9]. The main disadvantage is that there is no model that include all possible diseases [11]. Therefore, when new disease is added to the dataset, the CNN should be retrained with variations in training parameters to achieve the best possible results, which can be time consuming. Of course, datasets could be expanded with new classes of diseases. However, it can bring potential problem, since the different diseases can have similar symptoms, which makes it difficult for the CNN to successfully distinguish between them. The good side of the CNN implementation is that the developed systems can be integrated in mobile devices or embedded systems, making them easy to use [15]. Currently there are some limitations when it comes to the use networks with great number of parameters, as they cannot be run on mobile phone [17]. The solution for that problem is to use the lightweight CNN. Also, some technologies are very expensive [17]. Finally, CNNs can achieve great robustness if they are trained with many samples of data [21] but they do not achieve satisfactory accuracy when they are faced with multiple disease on one leaf [11] and [17].

6. CONCLUSION

Agriculture 4.0 should develop strategies to overcome numerous problems of the traditional agriculture, while making it easier to satisfy the demands of the growing population. This paper offers overview of the usage of CNN for the purpose of diagnosing corn and wheat diseases based on the images of plant's leaf, as it is important to take appropriate steps for their suppression as soon as possible. The most important points of this paper are given in the continuation.

Initially, the amount of production of plant species in Serbia was analyzed. It was shown that corn is unquestionably the most widely grown plant, following with the wheat and sugar beet.

When it comes to research papers based on the application of CNNs for the diagnosing of plant diseases significant for Serbian agricultural production, it can be seen that some plants are not taken into consideration at all. Also, some of them are not thoroughly analyzed in comparison with plants like apple, potato, grape, corn, which are often represented in research papers.

The result of the overview of studies about diagnosing wheat diseases shows that the best performance, with accuracy of 99.95%, is achieved by using custom network, RFE-CNN. This model is trained to classify four wheat leaf diseases and to recognize a healthy leaf. The most effective model in terms of the number of diseases it recognizes is differential amplification CNN with the accuracy of 99.18% and the ability to recognize seven leaf diseases and healthy leaf.

The outcome of this research also shows that for diagnosing three corn diseases and healthy leaf condition, the highest accuracy – 99.84% can be obtained by using EfficientNet-B0, while improved GoogLeNet can classify nine types of leaf images with the accuracy of 98.9%. Some models for diagnosing maize diseases are also tested in real-time, showing that proposed methods can give promising results, but because of real-time conditions, performance of those models cannot overcome performances of CNN models tested and trained on data from laboratory.

Additionally, this paper offers short overview of advantages and limitations of implementing CNN models for real-time usage. It is pointed out that CNNs have great potential to improve agricultural processes, but there is still a lot of shortcomings that need to be exceeded and a lot of space for upgrading existing techniques.

Finally, the main conclusion is that the significance of CNNs in terms of diagnosing plant diseases is on the rise due to the benefits they bring. Nevertheless, much more effort is needed in order to develop an optimal model that can successfully recognize a wide range of diseases. Evidently, there is a lot of space for further improvement, while special attention should be given to the plant species important for Serbian agriculture, such as raspberry, sour cherry, sunflower, etc.

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