International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

Image Recognition in Agriculture and Landscape Protection

Iftikhar B. Abbasov

Southern Federal University, Academy of Engineering and Technology, Department of Engineering Graphics and Computer Design, Taganrog, Russia
iftikhar_abbasov[at]mail.ru

Abstract: ***This paper provides an overview of some studies on image recognition of crops, plants and woodlands. For image recognition in these areas, various methods of preprocessing, computer vision, and deep learning are used. The publications on the recognition, classification of fruits and vegetables in orchards, on the automation of grain harvesting are considered, articles on the recognition of agricultural plants based on leaf images are analyzed. Articles on the development of mobile systems for monitoring and recognizing the process of growing mushrooms based on the "green house" technology for farms are presented. The work on recognition, classification of forests, water resources using hyperspectral analysis of satellite images is described.***

Keywords: perception, image recognition, recognition of images of fruits, fruits, leaves, plants, mushrooms, deep learning, computer vision, landscape recognition, hyperspectral analysis, remote monitoring.

1. Introduction

In everyday life, we no longer pay attention to the introduction of tracking and recognition systems in an urban environment. They are mainly related to road safety and public order. These systems are also actively used in various sectors of the national economy, including agriculture, to increase the economic efficiency of agricultural production. Mobile computer vision systems can assess the state of the crop, crop production, horticulture. They use image recognition techniques to classify objects and scenes using deep learning and computer vision. This paper presents an overview and analysis of some modern research in the field of image recognition of crops, plants and forests in order to assess the prospects for their application and future development.

1) Recognition of images of fruits: apples, pears

Deep learning technology is successfully applied in various fields of science and industry, ranging from computer vision to speech recognition. I would like to note that the issues of perception and recognition of images in art were considered by the author in [1]. In the field of image processing, deep learning is used for scene analysis and object detection. However, with increasing scene density, the task of analysis becomes more complicated.

Article [2] is devoted to the analysis of scene density in agriculture. Various popular deep neural networks for the analysis of dense agricultural scenes are described [3]. In the future, the effectiveness of this method is investigated in the recognition, detection, classification, calculation and assessment of yield. It is noted that the field of recognition of agricultural scenes using deep machine learning is still at an early stage, as an expanded database for the classification of various agricultural products is needed [4]. The work [5] presents data on the recognition of fruits of apples and pears based on the analysis of more than one hundred photographs of fruit trees (Fig. 1).

Figure 1: Analysis of the scene in agriculture when recognizing images of fruits in the garden [2], [5]

2) Kiwi fruit recognition

Recognition of agricultural products is not an easy task, especially few publications devoted to the recognition of kiwi fruit [6], [7]. Kiwi belongs to the fruit crops of the genus actinidia (Latin actinidia chinensis), which have the appearance of a tree-like liana native to China, due to its nutritional value it is widely cultivated throughout the world. In [8], color models are used for basic image processing with frequency domain expansion. After filtering the image, the characteristics of the trunk are determined, and a binocular stereo vision system is used for fetal recognition, which increases the determination of the location of objects (Fig. 2). Experimental studies show good results of the proposed algorithm.

Figure 2: Original photo of kiwi fruit, processing with edge recognition, image recognition result [8]

3) Automation of harvesting corn based on computer vision and plant recognition

In recent years, more and more work is automated in the agricultural sector. Due to the expansion of corn planting areas in various agricultural regions of the world, a situation arises for adapting the corn harvester to the specific harvesting conditions. Corn is a spring grain; when grown in different climatic conditions, the distance between the rows of corn changes [9].

The article [10] examines the method of image processing and mathematical calculation of the parameters of corn rows using a digital tracking camera (Fig. 3). The recognition process is based on a step-by-step image processing using mathematical methods to determine the distance between rows. Next, the cutting table of the maize harvester itself is calibrated. Technological innovations make it possible to automate the harvesting process and increase the efficiency of harvesting agricultural products.

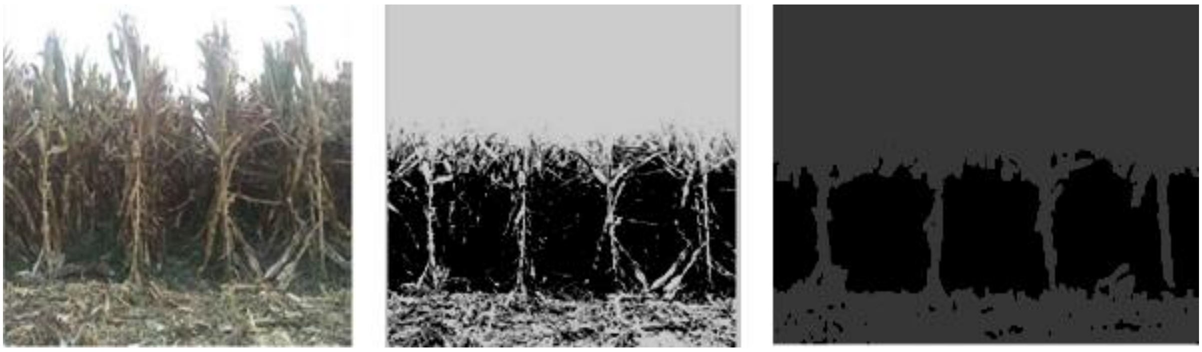

Figure 3: Stages of sequential image processing [10]

4) Leaf-based plant recognition and control

Non-woody plants and agricultural grasses provide households and farms with essential feed for livestock production. For effective growth, it is necessary to control the state of plants and their populations [11]. The use of the manual method of determination in modern conditions does not meet the requirements of the time, therefore, various methods of recognition and identification of plants are used based on the analysis of the characteristics of leaves. Work [12] is devoted to the development of mobile systems for the recognition and identification of plant species (Fig. 4). The paper studies the capabilities of various mobile systems for plant leaf recognition using smartphones.

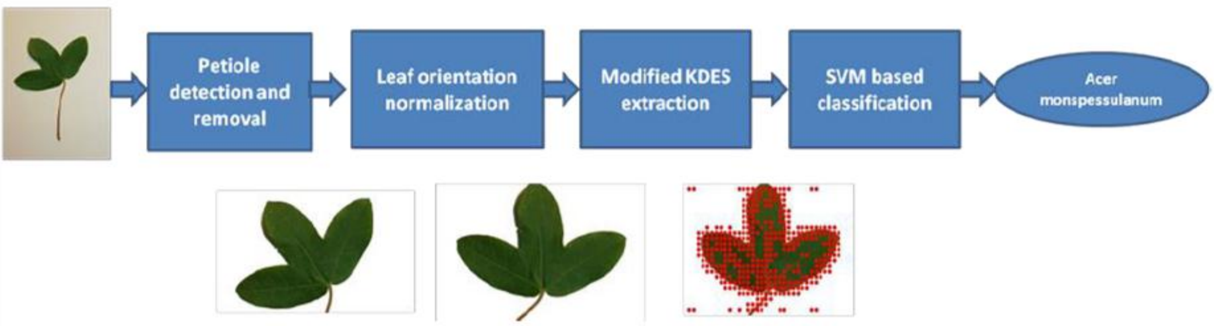

Figure 4: Methodology for the application of leaf-based plant identification [12], [13]

International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

In [14], various neural networks for recognizing flowers and leaves of plants are considered [15], [16]:
- Artificial neural network;
- Probabilistic neural network;
- Convolutional neural network;
- By the k-nearest neighbor method;
- Support for support vectors (support vector machine), and combined methods.

Using a variety of pretreatment methods improves the classification of the plant's leaf (Figure 5). The quality of the initial images of leaves plays an important role in their further recognition.

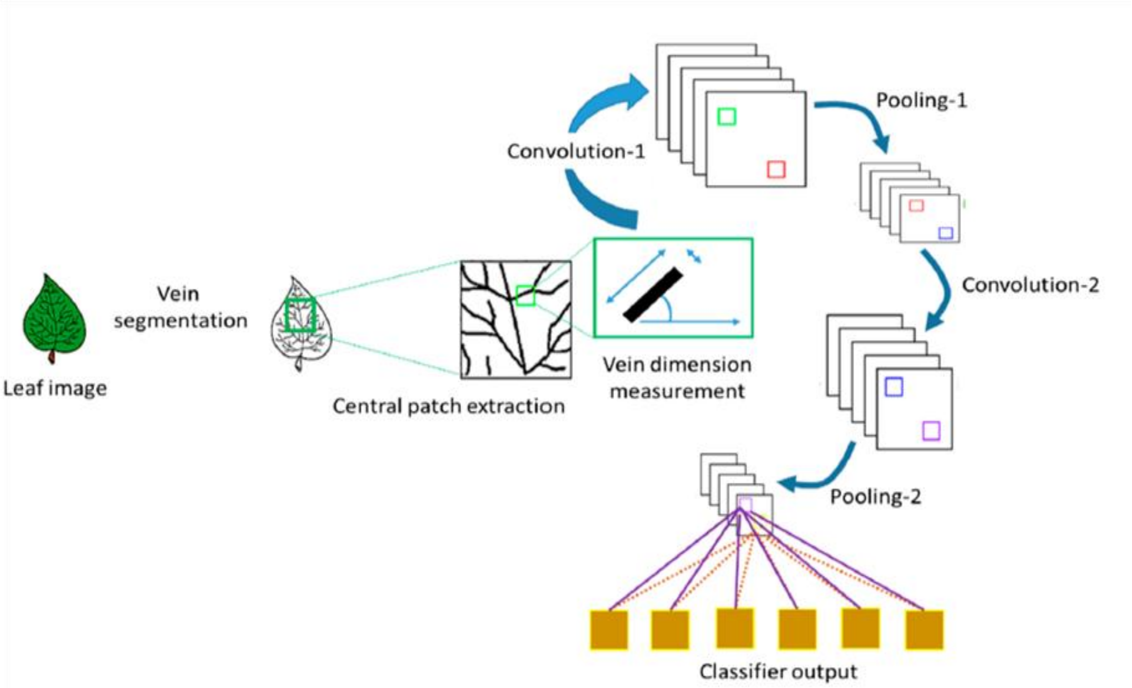

Figure 5: Recognizing leaf patterns using a convolutional neural network [14]

The work [17] is devoted to the analysis of tomato plant leaf disease using the ASD FieldSpec4 spectrometer. The Indian economy is heavily influenced by agriculture, and it is estimated that 30-35% of the crop is lost due to plant diseases. Using hyperspectral remote sensing, it is proposed to monitor the condition of plants, to identify diseases that are displayed within a narrow wavelength range. The developed technology is based on certain signs, attributes of plant diseases that are found in the spectrum of the reflected signal.

5) System for controlling the process of growing mushrooms

Today, mushrooms are an economically viable agricultural product with a high nutritional value. They are living organisms that combine the properties of plants and animals. Mushrooms play an important role in the life of the biosphere of our planet, processing organic materials, thereby increasing soil fertility. Due to global climate change, technological greenhouses are beginning to replace traditional methods of growing mushrooms. However, these greenhouses have a complex management structure [18]. The article [19] presents the development of a control system for growth and counting the number of mushrooms based on an intelligent convolutional neural network. The proposed system records data on mushrooms and transfers them to the farmer's mobile phone (Fig. 6), which increases the efficiency and effectiveness of production management.

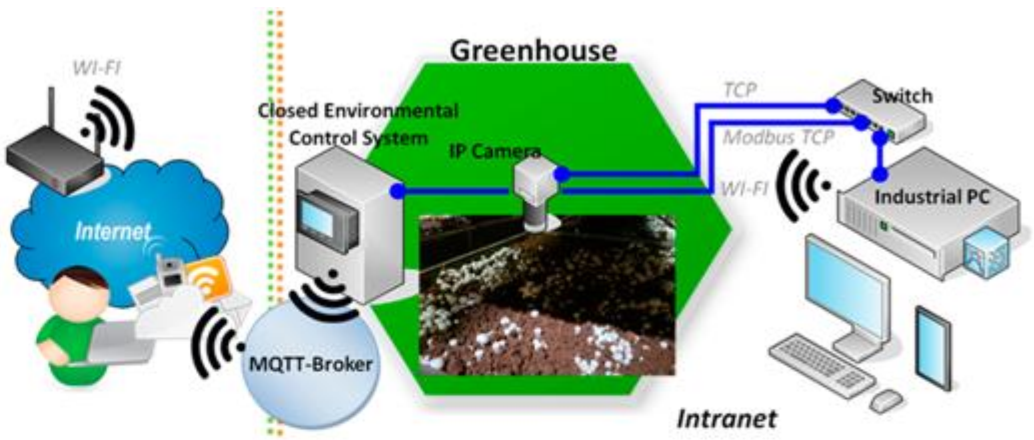

Figure 6: Communication structure for controlling the state of mushrooms [19]

6) Terrain recognition from satellite images

The article [20] compares satellite images of 1985 and 1996 (Fig. 7), which are used for visual interpretation of the mouth of the Brazilian river Rio Paraiba [21]. The comparison revealed the following differences: a change in the course of the Paraiba River at a distance of several kilometers, a change in the coastline as a result of ocean currents caused by the southeast trade winds, the constancy of boundaries between sugarcane fields, pastures and the remains of the original coastal forests, and the growth of urban areas. built-up areas.

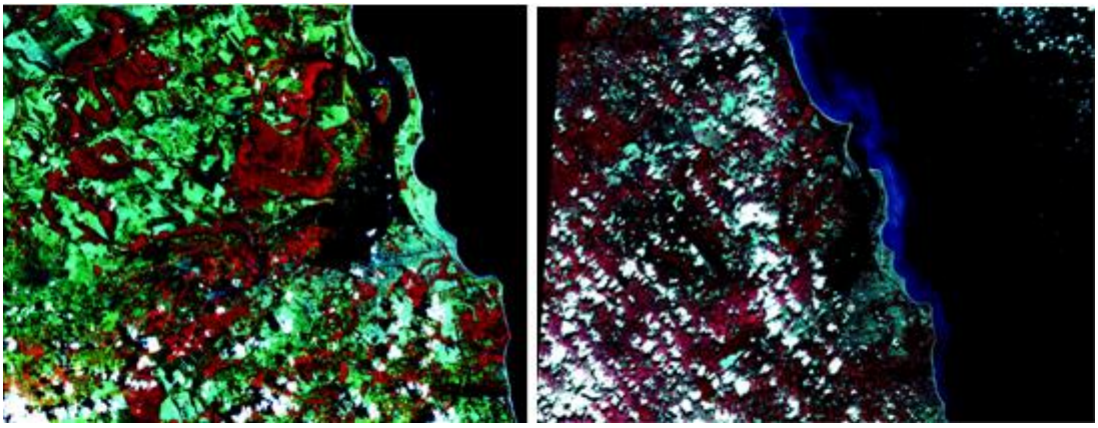

Figure 7: Satellite images of the mouth of the Rio Paraiba in 1985 and 1998 [20]

The genetic algorithm is designed to find the optimal solution by eliminating the worst case from gene sequences using the efficiency function [22]. This algorithm works well for classifying images with no detail. The article [23] proposes a new hybrid algorithm for improving the accuracy and reliability of the classification of satellite images. Using the example of an image of a reservoir, the effectiveness of the proposed method for recognizing land use objects is demonstrated (Fig. 8).

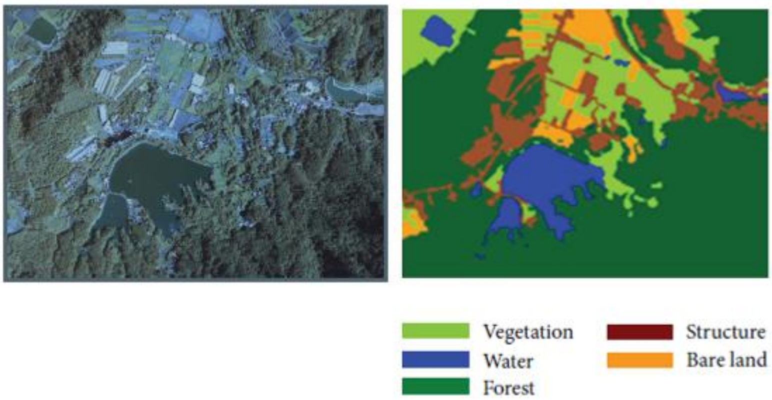

Figure 8: Aerial view of the area and the result of image analysis [23]

Remote sensing using satellites is often used to map the earth's surface and assess the ecological state. Every year the quality of satellite images increases, the resolution of these images increases [24]. Recognition, classification and detection of objects based on the deep learning method becomes more effective. The article [25] provides a detailed overview on the classification of the terrain of the earth's surface for object detection based on high-resolution images. Deep learning methods provide a comprehensive solution using spatial and spectral information (Figure 9). Especially for different types of vegetation, this method is more efficient and more accurate than the traditional pixel-based method.

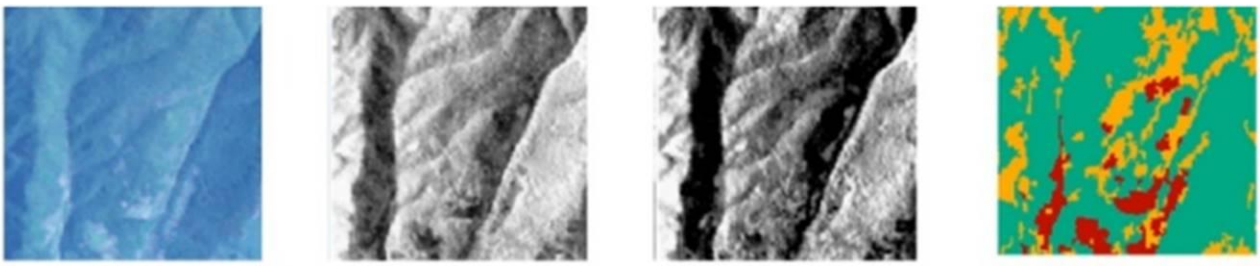

Figure 9: The terrain of the earth's surface in various versions for training the model: modes visible range, red edges, near infrared and in land cover labels [25]

The article [26] proposes an effective method for image classification during monitoring using an unmanned aerial vehicle. Aerial photographs of various landscapes containing forests, meadows, rivers and buildings are used as images. Information on color channels of textures containing static and fractal characteristics is used. The training system takes into account various parameters of objects to classify surface textures.

Article [27] is devoted to a review of methods for remote diagnostics of the earth's surface, especially the water part - the ocean surface. Based on remote analysis, it is possible to determine the state of the aquatic environment, identify physical parameters, estimate the temperature, based on color, determine the nutritional value of water masses, the content of biological resources.

7) Recognition of forest areas in hyperspectral images

Papers [28], [29], [30], [31] are devoted to algorithms for recognizing forest cover objects in hyperspectral aerospace images. When processing hyperspectral images, natural-man-made objects are recognized by their spectral and textural features. Examples of comparison of these classifiers, a metric classifier and a classifier based on the method of "k-weighted neighbors".

Figure 10, below, shows the result of recognition of the initial hyperspectral image by the developed method, where blue is water, yellow is sand, black is road surface, dark green is pine stands, light green is birch stands, orange is aspen stands, red is - herbaceous vegetation, purple - other objects.

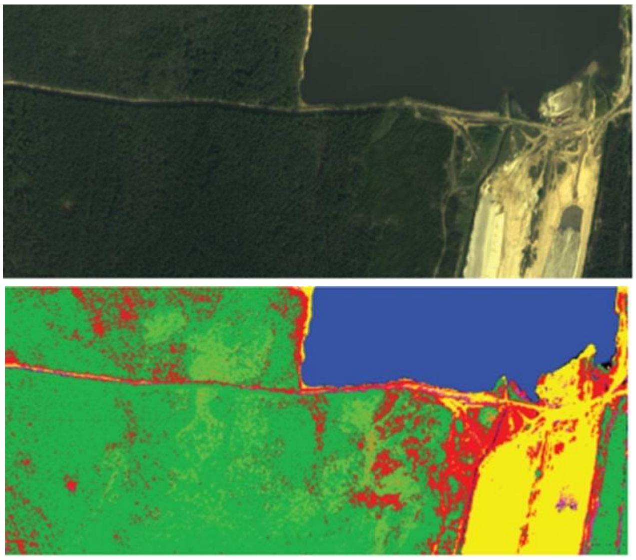

Figure 10: The original hyperspectral image and the result of object recognition on it using the method of "k-weighted neighbors" [28]

The work [32] is devoted to the analysis of the state of urban forest zones with the aim of monitoring the ecosystem by the method of remote sensing [33]. Remote sensing is used in three ways: different in source, different in time, and different in scale. The results of combined optical imaging and lidar data (LiDAR) are the most promising (Fig. 11). Fog removal techniques to improve the quality of satellite imagery.

Figure 11: Examples of fusion satellite imagery and LiDAR point cloud data at the district level of the city [32]

For environmental monitoring, it is effective to use hyperspectral imaging systems [34], [35]. In article [36], a mobile system of hyperspectral sensors for ground-based applications is being developed. These devices are becoming more compact and mobile, which increases their value for stand-alone monitoring (Figure 12). They facilitate access to hyperspectral monitoring technologies, significantly speeding up the data acquisition process.

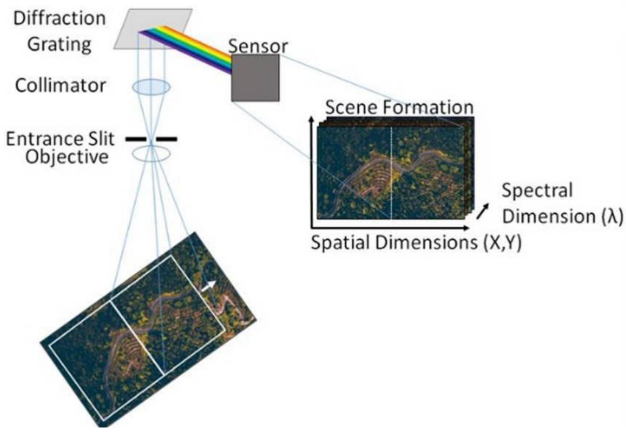

Figure 12: Remote sensing framing sensor circuit [36]

2. Research Analysis

The deep learning method is used quite often in recognition problems, for example, the classification of fruits and landscape objects on satellite images. This method becomes ineffective with an increase in the density of classified objects; an increase in the database for training is required.

For many classification cases, it becomes more efficient to combine preprocessing and further recognition methods based on neural networks. For hyperspectral images, a preliminary classification is carried out according to spectral and texture characteristics, further classification is carried out by the method of "k-weighted neighbors". In the case of remote diagnosis of the state of tomato plants, the frequency range is determined that characterizes diseases of the leaves.

For the tasks of recognition of kiwi fruits, preliminary processing is carried out using color models when determining the characteristics of the trunks, then a binocular machine stereo vision system is used to recognize kiwi fruits.

During the operation of the corn harvester, the distance between the rows is preliminarily determined based on the data from the digital tracking camera. To recognize flowers and leaves of plants, the developed mobile application uses preprocessing and further recognition using neural networks. Mushroom control smartphone mobile application uses intelligent Convolutional Neural Network.

Therefore, it can be noted that today neural networks are the most promising direction in pattern recognition and computer vision for solving various kinds of problems.

3. Conclusion

In this paper, some articles were considered on the issues of image recognition in the agricultural sector and monitoring of forest areas. Articles have been described on the development of methods for recognizing agricultural scenes with fruits, fruits and plants. Modern recognition systems based on mobile devices are noted. Remote sensing methods for monitoring a landscape with forest cover and water bodies based on hyperspectral analysis were also described. As a result of the analysis and prospects for the development of recognition systems, it can be noted that they all often adapt to the needs of individual users, farmers. The process of recognizing agricultural products takes place in real mode using applications for mobile devices. The emergence of such software developments will make it possible to increase the efficiency of agricultural production, speed up the process of management and implementation of mobile technologies.

References

[1] *Abbasov I.B.* Features of the Perception and Recognition of Images in Art: Review Article // International Journal of Science and Research (IJSR), 2020, V.9, Issue 6, P.368-375 doi:10.21275/SR20604144833

[2] *Zhang Q., Liu Y., Gong C., Chen Y., Yu H.* Applications of Deep Learning for Dense Scenes Analysis in Agriculture: A Review // Sensors 2020, V.20, 1520. 33p. doi:10.3390/s20051520

[3] *Bechar A., Vigneault C.* Agricultural robots for field operations: concepts and components // Biosyst. Eng. 2016, 149, P.94–111. doi:10.1016/j.biosystemseng.2016.06.014

[4] *Kelman E.E., Linker R.* Vision-based localisation of mature apples in tree images using convexity // Biosyst. Eng. 2014. V.118, P.174–185. doi:10.1016/j.biosystemseng.2013.11.007

[5] *Bresilla K., Perulli G.D., Boini A., Morandi B., Corelli Grappadelli L., Manfrini L.* Single-Shot Convolution Neural Networks for Real-Time Fruit Detection Within the Tree // Front. Plant Sci. 2019, V.10, 611. 12p. doi:10.3389/fpls.2019.00611

[6] *Yongjie C.* Recognition and feature extraction of kiwifruit in natural environment based on machine vision // Trans. Chin. Soc. Agric. Mach. 2013. 44(5), P.247–252

[7] *Fu L., Feng Y., Elkamil T. et al.* Image recognition method of multi-cluster kiwifruit in field based on convolutional neural networks // Trans. Chin. Soc. Agric. Eng. 2018. 34(2), P.205-211

[8] *Liu D., Shen J., Yang H. et al.* Recognition and localization of actinidia arguta based on image recognition // J Image Video Proc. 2019, 21p. doi:10.1186/s13640-019-0419-6

[9] *Shinners K.J., Boettcher G.C., Holfman D.S., et al.* Single-pass harvest of corn grain and stover: performance of three harvester configurations // Transactions of the ASABE, 2009, 52(1): P.51-60.

[10] *Song Xiangwen, Cao Shukun, Wang Chong, Xu Xiangqian, Han Tao and Guo Hejia.* Automatic 9 Row Corn Harvester Based on Labview Image Recognition // IOP Conf. Series: Journal of Physics: Conf. Series 1098, 2018, 012016 doi:10.1088/1742-6596/1098/1/012016

[11] *Sun Y., Liu Y., Wan, G., Zhang H.* Deep Learning for Plant Identification in Natural Environment" // Computational Intelligence and Neuroscience, 2017, Article ID 7361042, 6 p. https://doi.org/10.1155/2017/7361042

[12] *Shaikh N.A., Mallah G.A., Karaş,İ.R., Akay A.E.* Using mobile image recognition system for nonwood species identification in the field // Journal of Innovative Science and Engineering. 2018. 2(2): P.40-50. doi:10.38088/jise.498910

[13] *Le T., Tran D., Hoang V.* Fully automatic leaf-based plant identification, application for Vietnamese medicinal plant search // SoICT '14, December 04 – 05, 2014, Hanoi, Vietnam. https://doi.org/10.1145/2676585.2676592

[14] *Azlah M.A.F., Chua L.S., Rahmad F.R., Abdullah F.I., Wan Alwi S.R.* Review on Techniques for Plant Leaf Classification and Recognition // Computers 2019, V.8, 77. 22p.

[15] *Sabu A., Sreekumar K.* Literature review of image features and classifiers used in leaf based plant recognition through image analysis approach. In Proceedings of the 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 10–11 March 2017; P.145–149.

[16] *Munisami T., Ramsurn M., Kishnah S., Pudaruth S.* Plant Leaf Recognition Using Shape Features and Colour Histogram with K-nearest Neighbour Classifiers // Procedia Comput. Sci. 2015, 58, P.740–747

[17] *Sapate N.M., Deshmukh R.R.* Spectral and Numerical Analysis of Hyperspectral Data using Vegetation Indices // International Journal of Engineering and Advanced Technology, 2019. V.8, Issue-6, doi:10.35940/ijeat.F8578.088619

[18] *Wu W.-H., Zhou L., Chen J., Qiu Z., He Y., GainT.* A measurement system of thousand kernel weight based on the android platform // Agronomy, 2018,V.8, P.178-185

[19] *Lu C.-P., Liaw J.-J., Wu T.-C., Hung T.-F.* Development of a Mushroom Growth Measurement System Applying Deep Learning for Image

Recognition //Agronomy, 2019, V.9, 32. 21p. doi:10.3390/agronomy9010032
[20] *Ulbricht K.A, Heckendorff W.D.* Satellite images for recognition of landscape and landuse changes // ISPRS Journal of Photogrammetry and Remote Sensing, V.53, Issue 4, 1998, P.235-243, doi:10.1016/S0924-2716(98)00006-9
[21] *Teotia H.S., Ulbricht K.A., Civco D.L.* The integration of remote sensing and GIS technologies for land development and irrigation potential in the state of Ceara, Brazil. In: Proceedings of the XVII ISPRS Congress, Washington D.C. Int. Arch. Photogramm. Remote Sensing. 1992. 29 (B7), P.466–472
[22] *Bazi Y., Melgani F., Bruzzone L., Vernazza G*. A genetic expectation-maximization method for unsupervised change detection inmultitemporal SAR imagery, // International Journal of Remote Sensing, 2009. V.30, no. 24, P.6591–6610
[23] *Yang Ming-Der, Yeh-Fen Yang, Tung-Ching Su, and Kai-Siang Huang.* An Efficient Fitness Function in Genetic Algorithm Classifier for Landuse Recognition on Satellite Images // The Scientific World Journal, V. 2014, Article ID 264512, 12 p. doi.org/10.1155/2014/264512
[24] *Huang B., Zhao B., Song Y.* Urban land-use mapping using a deep convolutional neural network with high spatial resolution multispectral remote sensing imagery // Remote Sens. Environ. 2018, 214, P.73–86
[25] *Zhang X., Han L., Han L., Zhu L.* How Well Do Deep Learning-Based Methods for Land Cover Classification and Object Detection Perform on High Resolution Remote Sensing Imagery // Remote Sens. 2020, 12, 417. 29p. https://doi.org/10.3390/rs12030417
[26] *Popescu D., Ichim L.* Image Recognition in UAV Application Based on Texture Analysis. In: Battiato S., Blanc-Talon J., Gallo G., Philips W., Popescu D., Scheunders P. (eds) Advanced Concepts for Intelligent Vision Systems. ACIVS 2015. Lecture Notes in Computer Science, vol 9386. Springer, 2015. doi:10.1007/978-3-319-25903-1_60
[27] *Abbasov I.B., Deshmukh R.R.* Methods of remote diagnostic of water surface. In the Proceeding: “Computer and information technologies in science, engineering and management "ComTech-2019". Materials of the Russian scientific and technical conference with international participation. 2019. P.477-481.
[28] *Kozoderov V.V., Kondranin T.V., Dmitriev E.V.* Comparative analysis of recognition algorithms for forest cover objects on hyperspectral aerospace images // Earth exploration from space, 2016, No. 6, P.45–55 doi:10.7868/S020596141606004X
[29] *Kozoderov V.V., Dmitriev E.V.* Patterns of recognition and assessment of the state of forest vegetation from hyperspectral data of remote sensing // Research of the Earth from Space, 2017, No. 6, P.75–88, doi:10.7868/S0205961417060070
[30] *Kozoderov, V.V., Kondranin T.V., Dmitriev E.V.* Hyperspectral remote sensing imagery processing focused on forest applications // International Review of Aerospace Engineering. V.10, Issue 5, 2017, P.267-276
[31] *Kozoderov V.V., Egorov V.D.* Recognition of types of forest vegetation by hyperspectral aircraft and multi-channel satellite data of high spatial resolution. Comparison of results and assessment of their accuracy // Research of the Earth from Space, 2019, No. 6, P.89–102 doi:10.31857/S0205-96142019689-102
[32] *Li X., Chen W.Y., Sanesi G., Lafortezza R.* Remote Sensing in Urban Forestry: Recent Applications and Future Directions // Remote Sens. 2019, 11(10), 1144; 20p. doi:10.3390/rs11101144
[33] *Roman L.A., Pearsall H., Eisenman T.S., Conway T.M., Fahey R.T., Landry S., Vogt J., van Doorn N.S., Grove J.M., Locke D.H., et al.* Human and biophysical legacies shape contemporary urban forests: A literature synthesis Urban // For. Urban Green. 2018, 31, P.157–168
[34] *Govender M., Chetty K., Bulcock H.* A review of hyperspectral remote sensing and its application invegetation and water resource studies // Water SA, 2017, 33, P. 145–152.
[35] *Khan M.J., Khan H.S., Yousaf A., Khurshid K., Abbas A.* Modern trends in hyperspectral image analysis: A review // IEEE Access 2018, 6, P.14118–14129.
[36] *Stuart M.B., McGonigle A.J.S., Willmott J.R.* Hyperspectral Imaging in Environmental Monitoring: A Review of Recent Developments and Technological Advances in Compact Field Deployable Systems // Sensors 2019, 19, 3071. 17p. doi:10.3390/s19143071