DOI 10.15622/ia.21.4.3

A. MAHAMUDUL HASHAN, R. MD RAKIB UL ISLAM, K. AVINASH

APPLE LEAF DISEASE CLASSIFICATION USING IMAGE DATASET: A MULTILAYER CONVOLUTIONAL NEURAL NETWORK APPROACH

Mahamudul Hashan A., Md Rakib Ul Islam R., Avinash K. **Apple Leaf Disease Classification Using Image Dataset: a Multilayer Convolutional Neural Network Approach.**

Abstract. Agriculture is one of the prime sources of economic growth in Russia; the global apple production in 2019 was 87 million tons. Apple leaf diseases are the main reason for annual decreases in apple production, which creates huge economic losses. Automated methods for detecting apple leaf diseases are beneficial in reducing the laborious work of monitoring apple gardens and early detection of disease symptoms. This article proposes a multilayer convolutional neural network (MCNN), which is able to classify apple leaves into one of the following categories: apple scab, black rot, and apple cedar rust diseases using a newly created dataset. In this method, we used affine transformation and perspective transformation techniques to increase the size of the dataset. After that, OpenCV crop and histogram equalization method-based preprocessing operations were used to improve the proposed image dataset. The experimental results show that the system achieves 98.40% training accuracy and 98.47% validation accuracy on the proposed image dataset with a smaller number of training parameters. The results envisage a higher classification accuracy of the proposed MCNN model when compared with the other well-known state-of-the-art approaches. This proposed model can be used to detect and classify other types of apple diseases from different image datasets.

Keywords: artificial intelligence, apple leaf disease, image processing, multilayer convolutional neural network, classification.

1. Introduction. The cultivation area and production of apples in Russia are leading in the world, and it is one of Russia's most important economic crops [1]. Due to the economic growth, apple planting area and production increase every year. Global food security is threatened by climate change (a comprehensive analysis of the individual and combined effects of ozone trends on global climate change 2000-2050) [2] and plant diseases (at least 10% of the world's food production is lost due to plant diseases) [3]. In developing countries like Bangladesh, the identification of plant diseases is done by visual observation by the farmers, where proper identification of the diseases usually depends on the skill, experience, and ability of the farmers. There is always a risk of incorrect detection and classification of plant diseases. Sometimes, the agronomists may fail to properly identify leaf disease. This is a big challenge to accurately identify leaf disease, timely treat, and protect crop from damage.

In recent years, computer vision and deep learning techniques have been widely used in agriculture, and a number of methods for the identification of crop diseases have been acquired [4, 5]. Popular methods that are widely used to detect crop diseases include artificial neural network

(ANN) [6], K Nearest Neighbors (KNN) algorithm [7], and so on. There are several diseases that attack apples, the major ones are apple scab (*Venturia inaequalis*), Apple black rot (*Botryosphaeria obtusa*), and apple cedar rust (*Gymnosporangium juniperi-virginianae*). The proper care of apple trees using fertilizers can help the farmers. However, apple leaf diseases cause low production, financial losses, and a decrease in the quality of fruit industry products. Therefore, there is a necessity of accurate methods for detecting apple leaf diseases and preventing losses by taking proper actions.

To solve this problem, early detection of apple leaf diseases is necessary. Manual detection of apple leaf diseases is carried out either by farmers or agricultural scientists. Manual detection is a challenging and time-consuming task. To address this problem, many researchers around the world have introduced various state-of-the-art systems for automatic detection of apple leaf diseases through different machine learning [8, 9] and deep learning [10, 11] methods. However, these existing systems use a very high number of training parameters and a large number of datasets. Therefore, the training and prediction time of these systems is very long and requires high computing power. There are two noticeable advantages of deep learning methods over machine learning methods. First, they automatically extract various features from raw data, so there is no need for an additional feature extraction module. Second, deep learning methods reduce the time required to process large, high-dimensional datasets.

This paper proposes an MCNN model for automatic apple leaf disease classification with fewer training parameters. In addition, the research includes effective data augmentation and image preprocessing operations. The proposed method boosts the apple leaf disease recognition accuracy and reduces computational time. The rest of the paper is arranged into four sections. Section 2 discusses several state-of-the-art methods for the automatic detection and classification of apple leaf diseases described in the literature. In Section 3, the methods used to design the multilayer convolution neural network are described. The results from the apple leaf disease classification model are presented in Section 4 and Section 5 conclusions.

2. Related Works. Modern technology makes the agriculture sector more advanced by early disease detection and reduction of human efforts. There are various techniques for automated detection and classification systems using deep learning, such as brain tumor detection using MRI images [12], tomato crop disease classification using deep learning [13], and so on.

In order to improve the accuracy of deep neural networks, Xie et al. [14] proposed a real-time grape leaf disease detector using improved deep convolutional neural networks. Initially enlarges the grape leaf disease image using digital imaging technology and creates a grape leaf disease (GLDD) dataset. Based on GLDD and the Faster R-CNN detection algorithm, a deep learning-based Faster DR-IACNN model with a higher feature extraction capability for grape leaf disease detection is presented. The implemented detection model Faster DR-IACNN achieves a precision of 81.1% mAP on GLDD, and the detection speed reaches 15.01 FPS. Sun et al. [15] proposed three major steps to detect maize leaf blight diseases using a convolutional neural network. They recommended a way to consolidate dataset preprocessing, fine-tuning network, and detection module. They claimed in their paper, that data preprocessing reduced the influence of high-intensity light on image identification and improved accuracy. They used the loss function with Generalized Intersection Over Union (GIoU) to optimize the detection processes. The proposed model achieved the highest mean average precision (mAP) 91.83%. Sabrol et al. [16] proposed a system to identify tomato plant disease by using a tree classifier model from the tomato leaf image dataset. The classification was conducted by extracting color, shape and texture features from tomato plant images. Five types of tomato diseases and one healthy were classified which used 382 tomato images and overall 97.3% of classification accuracy was achieved.

Aiming at the complexity of identifying apple leaves disease, Yadav et al. [17] presented an automatic technique for apple leaves disease detection using a convolutional neural network. This model uses preprocessing and fuzzy c-mean clustering for the identification and classification of apple leaves disease. Authors claim that the proposed model provided overall 98% accuracy. Also, Baranwal et al. [18] presented an automatic technique for apple leaves disease detection using a convolutional neural network at SUSCOM-19 which was organized by Amity University in India. The dataset with 1000 samples of healthy leaf image and 1526 unhealthy leaf images are used in their project. Image Compression and filtering techniques with convolutional neural networks are used for the automatic identification of apple leaves disease. The convolutional neural network model is used similarly to the LetNet architecture and the proposed model has offered 98.54% apple leaves disease detection accuracy.

Traditional deep learning methods have large progress in the leaf disease recognition field. Bin Liu et al. [19] introduced a novel architecture of a deep convolutional neural network based on AlexNet for the identification of apple leaves diseases using a dataset that included 13689 images. The Google Net’s inception is utilized to enhance and boost the feature extraction ability. The image processing techniques are applied to avoid overfitting in the training processes. Nesterov's Accelerated Gradient (NAG) optimization algorithm is applied to train the CNN-based model. This proposed novel CNN model architecture automatically detects leaf diseases with 97.62% accuracy. Kerkech et al. [20] proposed a model for automatic vine disease detection using the registration method on Unmanned Aerial Vehicle (UAV) image dataset. Also, they used a traditional CNN model to classify each pixel according to different instances. They claimed that the proposed method achieved more than 92% of apprehension at the level of grapevine and 87% at the leaf level.

Sanga et al. [21] proposed a disease detection application for banana plants using five different convolutional neural network architectures (VGG-16, ResNet-152, ResNet-50, ResNet-18, and InceptionV3). They found that ResNet-152 architecture performed an accuracy of 99.2%, which is better than other models. They also proposed a mobile application, so that farmers could easily detect diseases by uploading banana leaf images with their smartphones. Chohan et al [22] proposed a similar work using VGG-19 and InceptionV3 CNN architectures for automatic plant disease detection and classification using the PlantVillage image dataset. They used data augmentation to enlarge the dataset. They claimed in their paper, that the VGG-19 model performed with 98% training accuracy, and the InceptionV3 model performed with 95% testing accuracy.

Dealing with YOLO architecture, Wu et al. [23] introduced the YOLOv4 model and data augmentation methods for the apple picking robot to identify apples quickly and accurately. They used EfficientNet architecture and convolution layer (Conv2D), instead of Cross Stage Partial Darknet53 (CSPDarknet53) due to the extensive size and calculation of the YOLOv4 Model. The apple identification is performed on 2670 samples and the test result shows that the EfficientNet-B0-YOLOv4 model is better than YOLOv3, YOLOv4, and Faster R-CNN. The proposed EfficientNet-B0-YOLOv4 model offers accurate identification results, and it can be used for the vision system of picking robots in the apple industry. Coulibaly et al. [24] introduced a disease detection system for millet crops in the agricultural sector. Their approach was used to extract millet crops leaf's features based on the transfer learning technique of the neural network model. The test dataset used to evaluate the performance of the model includes 18 images with diseases and 9 images without diseases. A pre-trained VGG16 model had been used to transfer its learning ability to their proposed CNN network, where the best accuracy achieved 95%, precision of 90.50%, recall of 94.50% and the f1-score of 91.75%.

In this study, we proposed a multilayer convolutional neural network

(MCNN), data augmentation methods, and image preprocessing methods to overcome the drawbacks of the previous methods and provide a practical solution. The limitations of the previous study and the main contributions of this study are summarized as follows:

1. The previous models have limitations in properly taking advantage of data augmentation techniques. The proposed model uses various image augmentation techniques such as affine transformation and perspective transformation to enhance the proposed dataset.

2. All of the studies reviewed above used a large number of learning parameters. Training a model with a large number of training parameters requires high computing power. Proposed multilayer convolutional neural network that reduces the dimensionality of the input of apple leaf images using image preprocessing operations such as the OpenCV crop method and the histogram equalization method. Reducing the dimension of apple leaf images before classification reduces the number of training parameters.

3. Material and Methods. This section discusses the materials and methods that elaborate the proposed model. Figure 1 shows the flow diagram of the overall systems, which lists the main steps. The detailed work of these processes is presented in the following subsections.

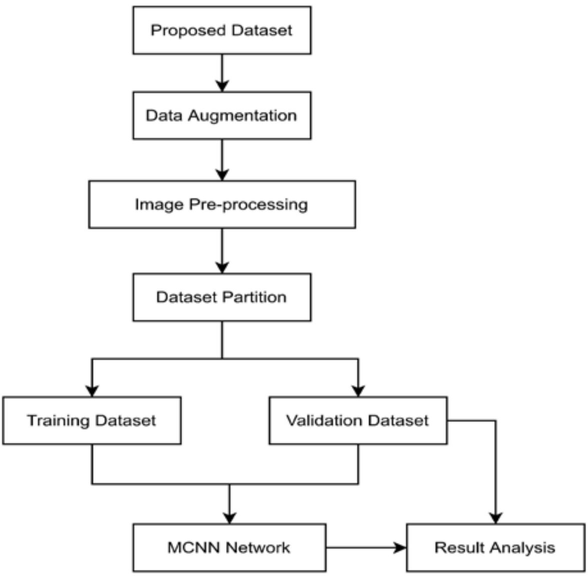

Fig. 1. Workflow for the whole system

3.1. Proposed Dataset. Dataset is one of the most important parts of a training network; we analyzed 480 images of apple leaves with high resolution. All the images collected for the dataset were downloaded from the Internet and searched for apple leaf diseases from various sources in different languages such as English, Russian, Bengali, and Hindi. The images in the dataset were grouped into three different classes. The dataset images consist of apple black root, apple cedar rust, and apple scab which are three common apple leaf diseases (Figure 2).

In order to avoid duplicate images, the comparing procedure was applied to remove duplicate apple leaf images using a developed python script. The script removed all duplicate apple leaf images by comparing metadata such as image name, size, and date. After that, the images were evaluated by human experts. The next step was to increase the apple leaf images dataset with augmented images. The main idea of this study is to train MCNN to learn the features of apple leaf images. Therefore, the chance to learn appropriate features was increased by using more augmented apple leaf images for the MCNN network. The image data augmentation process is described in Section 3.2. Finally, an apple leaf image dataset containing 3840 augmented images and 1141 images for validation has been created (Table 1). All apple leaf images are in RGB color and JPG format.

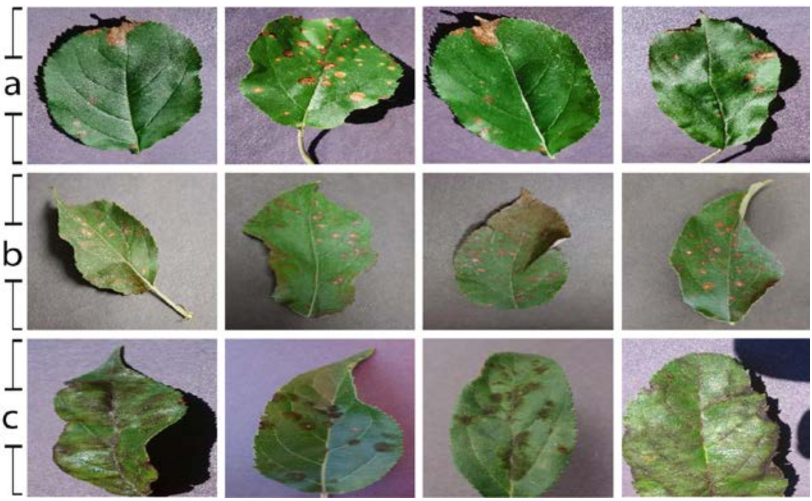

Fig. 2. Apple leaf disease images from the proposed dataset: (a) apple black rot leaves; (b) apple cedar rust leaves; (c) apple scab leaves

3.2. Data Augmentation. The main purpose of using data augmentation is to enlarge the dataset and introduce slight distortions in images, which helps to reduce overfitting during the training phase. OpenVX supports two commonly used image enlargement methods, which are affine transformation and perspective transformation [25]. In the affine transformation, we need three points from the input images and their corresponding locations in the output images. Affine transformation creates an $a^{2\times3}$ matrix, which defines a pixel coordinate mapping from the output to the input image following Equation (1):

$$\begin{aligned} x_0 &= M_{1,1}x + M_{2,1}y + M_{3,1}, \\ y_0 &= M_{1,2}x + M_{2,2}y + M_{2,3}. \end{aligned} \tag{1}$$

Where, x_0, y_0 and x, y = coordinates of a pixel in the input and output images, and M = affine matrix. Perspective transformation creates a 3×3 transformation matrix. It requires 4 points in the input image and corresponding points in the output image. The perspective transformation is defined by an $a^{3\times3}$ matrix following Equation (2).

$$\begin{aligned} x_u &= M_{1,1}x + M_{2,1}y + M_{3,1}, \\ y_u &= M_{1,2}x + M_{2,2}y + M_{2,3}, \\ z_u &= M_{1,3}x + M_{2,3}y + M_{3,3}. \end{aligned} \tag{2}$$

Where, x, y = pixel coordinates of the output image, and x_u, y_u, z_u = uniform pixel coordinates of the input image. These two transformations are applied in the proposed dataset (Figure 3), where the first image is an affine transformation; the second image represents a perspective transformation.

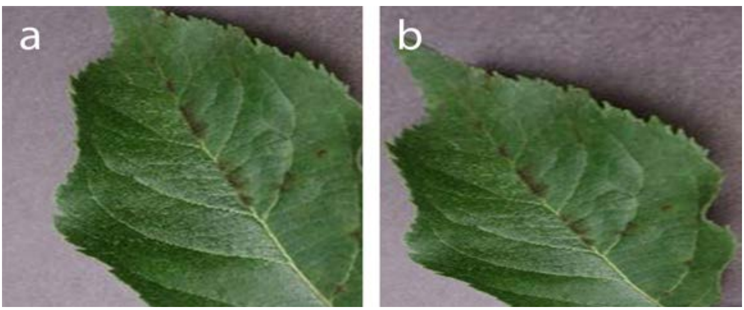

Fig. 3. Image transformations used for augmentation: (a) affine transformation; (b) perspective transformation

Table 1 shows the diseases along with the number of original images and the number of augmented images for each class. Additionally, it shows validation images for the disease classification model. Separating the data into training and test sets helps us find the best model and prevent overfitting. We run the experiments across a whole range of train-validation sets (where, 80% of the whole dataset is used for training, and the rest 20% for validation).

Table 1. Dataset for image classification of apple leaf disease

Disease Class	Original Images	Augmented Images	Validation Images
Apple Black Rot	170	1360	228
Apple Cedar Rust	160	1280	114
Apple Scab	150	1200	285
Total	480	3840	1141

3.3. Image Preprocessing. Preprocessing is a familiar name for operation on images, and it helps to improve the image data for further processes. The two different methods are used in the preprocessing stage, namely the OpenCV crop method for resizing the images and the histogram equalization method for contrast enhancement. The images captured may have different shapes and proportions, so the pictures are preprocessed and taken to the same size, removing noise, background, and distortions. The dimension of the input image is 256 × 256 to reduce the training time. So we resized our image dataset to 256 × 256 using the OpenCV 3.4.3 with Python 3.7 framework [26]. Further, the contrast of the apple leaf images is improved using the histogram equalization method [27] following Equation (3).

$$H(P_{(x,y)}) = \text{round}\ (\frac{f_{cdf}\,(p_{(x,y)}) - f_{cdf_{Min}}}{(R \times C) - f_{cdf}} \times L - 1)\ . \qquad (3)$$

Where, f_{cdf} = cumulative frequency, $f_{cdf_{min}}$ = minimum value of cumulative function, $f_{cdf}(p_{x,y})$ = intensity of current pixel, $R \times C$ = product of the number of pixels in rows and columns, and L = number of intensities.

3.4. MCNN Network Model. Convolutional neural networks which are specifically designed to deal with 2D shapes were first introduced by Lecun et al. in 1998 [28]. The proposed multilayer convolutional neural network (MCNN) consists of convolution layers, batch normalization layers, ReLU layers, max-pooling layers, and fully connected and softmax layers. The MCNN model has three blocks; the first block includes convolution, batch normalization, ReLU activation function, and max-pooling layers. The rest of the blocks include a convolution layer, ReLU function, max-pooling followed by a fully connected layer, and a softmax layer as shown in Figure 4.

The convolution operation was used to extract features such as color and edges from an apple leaf image. In this work, the size of the filter has been fixed in all the convolution layers, but the number of filters has been changed. In the first convolution layer, the number of filters is 8, while in the second and third convolution layers are 16 and 32 respectively. The main function of these layers is to extract properties from the input image. The batch normalization layer was used to speed up the training of multilayer convolutional neural networks and reduce the sensitivity for network initialization. Rectified Linear Unit (ReLU) activation function has been used to eliminate negative values, which can be represented by Equation (4) [29].

$$f(x) = \begin{cases} 0 & for\ x \le 0 \\ x & for\ x > 0 \end{cases} = \max\{0, x\} = x1_{x > 0}. \tag{4}$$

The max-pooling layer contains parameters such as the number of filters and the number of step sizes, which were used to reduce samples by choosing the maximum value and excluding the remaining value. The features were extracted from convolution1, Relu1, max-polling1, convolution2, Relu2, max-polling2, convolution3, Relu3, max-polling3. The fully connected layer belongs to the three classes of apple leaf diseases in this work. The class number represents the number of neurons used to connect each input to all neurons. The softmax function has been used to calculate the probability of each target class with the range from 0 to 1. It returns the probabilities for each class and the target class, which have a more high probability.

In order to verify the performance, the proposed network is trained using the apple leaf disease identification dataset [30]. It includes a set of 5461 images of apple black root, apple cedar rust, and apple scab leaves. The proposed method is experimented with using Google Colab (Jupyter Notebook) deep learning framework with a single 12GB NVIDIA Tesla K80 GPU.

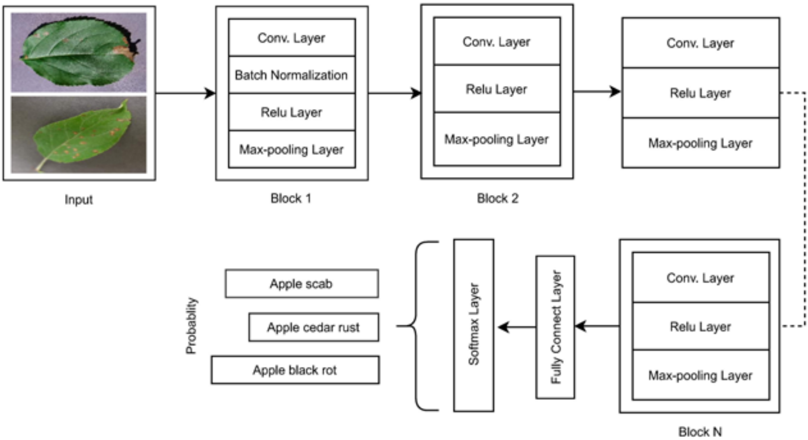

Fig. 4. The architecture of the proposed multilayer convolutional neural network

Other programming languages can be used such as Matlab, R, etc., to implement the proposed MCNN model. To train the MCNN network, the Adam optimizer [31] has been used with a batch size of 10 and 40 epochs. The training hyper-parameters used in this experiment are shown in Table 2.

Table 2. Training parameters of the proposed MCNN model

Parameter	Description
Number of epoch	40
Learning rate	1e-3
Batch Size	10
Steps	100
Optimizer	Adam (adaptive moment estimation)

4. Results and Discussion. This section discusses the results of the proposed method as part of the current research work. The performance of the proposed model is assessed by accuracy and confusion matrices are shown, and the necessary conclusions are drawn. The proposed MCNN model has achieved a training accuracy of 98.40% and a testing accuracy of 98.47%, with 0.05 training loss and 0.03 testing loss. The changes in training and testing loss, along with training and testing accuracy with respect to epochs, are shown in Figure 5. Accuracy is the number of accurate predictions regarding the total predictions made by a model.

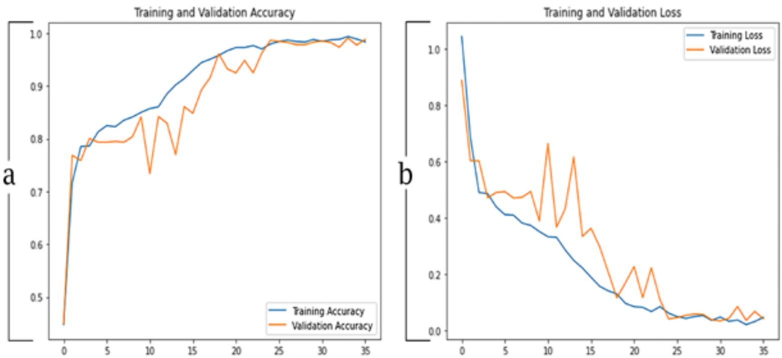

Fig. 5. Accuracy and loss graphs during model trainings: (a) training and validation accuracy; (b) training and validation loss

In addition, the performance of the MCNN model is shown using the Confusion Matrix Method (CMM) on the proposed dataset (Figure 6). The CMM method was applied to evaluate the classification accuracy for each class. The proposed MCNN model correctly predicts an average of 90 images out of 100 images. Also, the CMM method can be used to find the True Positive and False Positive Rates according to Equation (5) and Equation (6) [32].

$$True\ Positive\ Rate = \frac{True\ Positives}{True\ Positives + False\ Negatives} \times 100\%, \quad (5)$$

$$False\ Positive\ Rate = \frac{True\ Positives}{True\ Positives + True\ Negatives} \times 100\%. \quad (6)$$

From Table 3, it can be observed that the proposed MCNN model achieved 98.47% testing accuracy, which is more than the testing accuracies in the research works done by Khamparia et al. [33], with a testing accuracy of 86.78%, Tiwari et al. [34], with a testing accuracy of 97.8%, and Mohameth et al. [35], with a testing accuracy of 98%. The testing accuracy of the proposed model is slightly lesser than the testing accuracies in the research works done by Ferentinos [36] with a testing accuracy of 99.5%. However, in the proposed work only 688,315 training parameters are used, which is much less as compared to the number of training parameters in the state-of-the-art systems. The proposed model can be used for automatic plant disease detection on low computational power systems with less training time and prediction time.

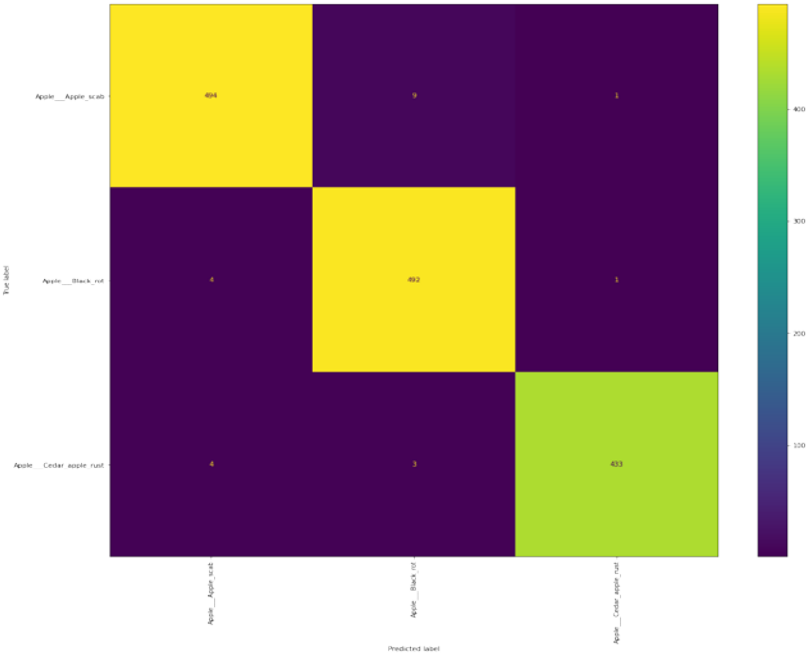

Fig. 6. Confusion Matrix for proposed MCNN model

Table 3. Comparison of different state-of-the-arts with the proposed model

Author's name and year	Proposed approach	Testing accuracy	Training parameters
Proposed approach	MCNN	98.47%	688,315
Khamparia et al. (2020)	Convolutional Encoder Network	86.78%	3.3 million
Tiwari et al. (2020)	VGG-19 + SVM	97.8%	143 million
Mohameth et al. (2020)	ResNet-50 + SVM	98%	25 million
Ferentinos (2018)	VGGNet	99.5%	138 million

5. Conclusion. This paper has presented an automated apple leaf disease classification using a multilayer convolutional neural network model. The MCNN model uses apple leaf images to determine the existence of disease with the highest detection rate of apple leaves. The proposed model encompasses the OpenCV crop method and histogram equalization method based on image preprocessing, affine transformation and perspective transformation-based augmentation, adaptive moment estimation-based parameter optimization, and MCNN-based classification.

The experimental outcome has shown the higher performance of this work compared to other methods. Also, acceptable results have been achieved. It’s indicated that deep learning is a significant method for leaf disease classification.

In the future, the detection efficiency of the MCNN method will be improved by the utilization of advanced deep learning-based image classification techniques with a web application for a real-time disease monitoring system. Additionally, we intend to expand our dataset to include more apple leaf images in order to build better models for the future.

References

1. A.I. Kuzin, N.Ya. Kashirskaya, A.M. Kochkina, and A.V. Kushner, “Correction of Potassium Fertigation Rate of Apple Tree (Malus domestica Borkh.) in Central Russia during the Growing Season,” Plants, vol. 9, no. 10, p. 1366, Oct. 2020, doi: 10.3390/plants9101366.
2. A.P. K. Tai, M.V. Martin, and C.L. Heald, “Threat to future global food security from climate change and ozone air pollution,” Nature Clim Change, vol. 4, no. 9, pp. 817–821, Sep. 2014, doi: 10.1038/nclimate2317.
3. R.N. Strange and P.R. Scott, “Plant Disease: A Threat to Global Food Security,” Annu. Rev. Phytopathol., vol. 43, no. 1, pp. 83–116, Sep. 2005, doi: 10.1146/annurev.phyto.43.113004.133839.
4. K.R. Aravind, P. Raja, K.V. Mukesh, R. Aniirudh, R. Ashiwin, and C. Szczepanski, “Disease classification in maize crop using bag of features and multiclass support vector machine,” in 2018 2nd International Conference on Inventive Systems and Control (ICISC), Coimbatore, Jan. 2018, pp. 1191–1196. doi: 10.1109/ICISC.2018.8398993.
5. V.P. Kour and S. Arora, “Particle Swarm Optimization Based Support Vector Machine (P-SVM) for the Segmentation and Classification of Plants,” IEEE Access, vol. 7, pp. 29374–29385, 2019, doi: 10.1109/ACCESS.2019.2901900.
6. M. Sheikhan, M. Pezhmanpour, and M.S. Moin, “Improved contourlet-based steganalysis using binary particle swarm optimization and radial basis neural networks,” Neural Comput & Applic, vol. 21, no. 7, pp. 1717–1728, Oct. 2012, doi: 10.1007/s00521-011-0729-9.
7. N. Guettari, A.S. Capelle-Laize, and P. Carre, “Blind image steganalysis based on evidential K-Nearest Neighbors,” in 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, AZ, USA, Sep. 2016, pp. 2742–2746. doi: 10.1109/ICIP.2016.7532858.
8. P. Bedi and P. Gole, “Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network,” Artificial Intelligence in Agriculture, vol. 5, pp. 90–101, 2021, doi: 10.1016/j.aiia.2021.05.002.
9. S. Chakraborty, S. Paul, and Md. Rahat-uz-Zaman, “Prediction of Apple Leaf Diseases Using Multiclass Support Vector Machine,” in 2021 2nd International Conference on Robotics, Electrical and Signal Processing Techniques (ICREST), DHAKA, Bangladesh, Jan. 2021, pp. 147–151. doi: 10.1109/ICREST51555.2021.9331132.
10. Y. Zhong and M. Zhao, “Research on deep learning in apple leaf disease recognition,” Computers and Electronics in Agriculture, vol. 168, p. 105146, Jan. 2020, doi: 10.1016/j.compag.2019.105146.
11. P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, “Real-Time Detection of Apple Leaf

Diseases Using Deep Learning Approach Based on Improved Convolutional Neural Networks," IEEE Access, vol. 7, pp. 59069–59080, 2019, doi: 10.1109/ACCESS.2019.2914929.

12. A.M. Hashan, E. Agbozo, A.A.K. Al-Saeedi, S. Saha, A. Haidari, and M.N.F. Rabi, "Brain Tumor Detection in MRI Images Using Image Processing Techniques," in 2021 4th International Symposium on Agents, Multi-Agent Systems and Robotics (ISAMSR), Batu Pahat, Malaysia, Sep. 2021, pp. 24–28. doi: 10.1109/ISAMSR53229.2021.9567799.
13. A.K. Rangarajan, R. Purushothaman, and A. Ramesh, "Tomato crop disease classification using pre-trained deep learning algorithm," Procedia Computer Science, vol. 133, pp. 1040–1047, 2018, doi: 10.1016/j.procs.2018.07.070.
14. X. Xie, Y. Ma, B. Liu, J. He, S. Li, and H. Wang, "A Deep-Learning-Based Real-Time Detector for Grape Leaf Diseases Using Improved Convolutional Neural Networks," Front. Plant Sci., vol. 11, p. 751, Jun. 2020, doi: 10.3389/fpls.2020.00751.
15. J. Sun, Y. Yang, X. He, and X. Wu, "Northern Maize Leaf Blight Detection Under Complex Field Environment Based on Deep Learning," IEEE Access, vol. 8, pp. 33679–33688, 2020, doi: 10.1109/ACCESS.2020.2973658.
16. H. Sabrol and K. Satish, "Tomato plant disease classification in digital images using classification tree," in 2016 International Conference on Communication and Signal Processing (ICCSP), Melmaruvathur, Tamilnadu, India, Apr. 2016, pp. 1242–1246. doi: 10.1109/ICCSP.2016.7754351.
17. D. Yadav, Akanksha, and A.K. Yadav, "A Novel Convolutional Neural Network Based Model for Recognition and Classification of Apple Leaf Diseases," TS, vol. 37, no. 6, pp. 1093–1101, Dec. 2020, doi: 10.18280/ts.370622.
18. S. Baranwal, S. Khandelwal, and A. Arora, "Deep Learning Convolutional Neural Network for Apple Leaves Disease Detection," SSRN Journal, 2019, doi: 10.2139/ssrn.3351641.
19. B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks," Symmetry, vol. 10, no. 1, p. 11, Dec. 2017, doi: 10.3390/sym10010011.
20. M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach," Computers and Electronics in Agriculture, vol. 174, p. 105446, Jul. 2020, doi: 10.1016/j.compag.2020.105446.
21. S.L. Sanga, D. Machuve, and K. Jomanga, "Mobile-based Deep Learning Models for Banana Disease Detection," Eng. Technol. Appl. Sci. Res., vol. 10, no. 3, pp. 5674–5677, Jun. 2020, doi: 10.48084/etasr.3452.
22. Department of Computer Science, Sukkur IBA University, Pakistan. et al., "Plant Disease Detection using Deep Learning," IJRTE, vol. 9, no. 1, pp. 909–914, May 2020, doi: 10.35940/ijrte.A2139.059120.
23. L. Wu, J. Ma, Y. Zhao, and H. Liu, "Apple Detection in Complex Scene Using the Improved YOLOv4 Model," Agronomy, vol. 11, no. 3, p. 476, Mar. 2021, doi: 10.3390/agronomy11030476.
24. S. Coulibaly, B. Kamsu-Foguem, D. Kamissoko, and D. Traore, "Deep neural networks with transfer learning in millet crop images," Computers in Industry, vol. 108, pp. 115–120, Jun. 2019, doi: 10.1016/j.compind.2019.02.003.
25. F. Brill, V. Erukhimov, R. Giduthuri, and S. Ramm, "Basic image transformations," in OpenVX Programming Guide, Elsevier, 2020, pp. 85–123. doi: 10.1016/B978-0-12-816425-9.00012-7.
26. S. Gollapudi, "OpenCV with Python," in Learn Computer Vision Using OpenCV, Berkeley, CA: Apress, 2019, pp. 31–50. doi: 10.1007/978-1-4842-4261-2_2.
27. H. Ali, M.I. Lali, M.Z. Nawaz, M. Sharif, and B.A. Saleem, "Symptom based

automated detection of citrus diseases using color histogram and textural descriptors," Computers and Electronics in Agriculture, vol. 138, pp. 92–104, Jun. 2017, doi: 10.1016/j.compag.2017.04.008.

28. Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proc. IEEE, vol. 86, no. 11, pp. 2278–2324, Nov. 1998, doi: 10.1109/5.726791.
29. A.F. Agarap, "Deep Learning using Rectified Linear Units (ReLU)," arXiv:1803.08375 [cs, stat], Feb. 2019, Accessed: Dec. 13, 2021. [Online]. Available: http://arxiv.org/abs/1803.08375
30. Antor Mahamudul Hashan, "Apple Leaf Diseases." Kaggle. doi: 10.34740/KAGGLE/DSV/2068940.
31. D.P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," 2014, doi: 10.48550/ARXIV.1412.6980.
32. R.R.O. Al-Nima, S.S. Dlay, W.L. Woo, and J.A. Chambers, "A novel biometric approach to generate ROC curve from the Probabilistic Neural Network," in 2016 24th Signal Processing and Communication Application Conference (SIU), Zonguldak, Turkey, May 2016, pp. 141–144. doi: 10.1109/SIU.2016.7495697.
33. A. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari, and V.H.C. de Albuquerque, "Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder Network," Circuits Syst Signal Process, vol. 39, no. 2, pp. 818–836, Feb. 2020, doi: 10.1007/s00034-019-01041-0.
34. D. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, and S. Bhardwaj, "Potato Leaf Diseases Detection Using Deep Learning," in 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, May 2020, pp. 461–466. doi: 10.1109/ICICCS48265.2020.9121067.
35. F. Mohameth, C. Bingcai, and K.A. Sada, "Plant Disease Detection with Deep Learning and Feature Extraction Using Plant Village," JCC, vol. 08, no. 06, pp. 10–22, 2020, doi: 10.4236/jcc.2020.86002.
36. K.P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.

Mahamudul Hashan Antor — Ph.D., Teacher assistant, Institute of fundamental education, Ural Federal University (UrFU). Research interests: intelligent information technologies; design, development and application of innovative software systems. The number of publications — 7. mantor@urfu.ru; 19, Mira St., 620002, Yekaterinburg, Russia; office phone: +7(962)316-1100.

Md Rakib Ul Islam Rizu — Graduate student, Ural Federal University (UrFU). Research interests: deep learning, machine learning. mdrakibulislam.rizu@urfu.me; 19, Mira St., 620002, Yekaterinburg, Russia; office phone: +7(965)545-09-44.

Avinash Kumar — Graduate student, Department of computer science, Ural Federal University (UrFU). Research interests: deep learning, machine learning. avinash.kumar@urfu.me; 19, Mira St., 620002, Yekaterinburg, Russia; office phone: +7(919)397-64-01.

УДК 004.056 **DOI** 10.15622/ia.21.4.3

А. Махмудул Хасан, Р. Мд Ракиб Ул Ислам, К. Авинаш

КЛАССИФИКАЦИЯ БОЛЕЗНЕЙ ЛИСТЬЕВ ЯБЛОНИ С ИСПОЛЬЗОВАНИЕМ НАБОРА ДАННЫХ ИЗОБРАЖЕНИЙ: ПОДХОД МНОГОСЛОЙНОЙ СВЕРТОЧНОЙ НЕЙРОННОЙ СЕТИ

Махмудул Хасан А., Мд Ракиб Ул Ислам Р., Авинаш К. **Классификация болезней листьев яблони с использованием набора данных изображений: подход многослойной сверточной нейронной сети.**

Аннотация. Сельское хозяйство является одним из основных источников экономического роста в России; мировое производство яблок в 2019 году составило 87 миллионов тонн. Болезни листьев яблони являются основной причиной ежегодного сокращения производства яблок, что приводит к огромным экономическим потерям. Автоматизированные методы выявления болезней листьев яблони позволяют сократить трудоемкую работу по мониторингу яблоневых садов и раннему выявлению симптомов болезни. В этой статье предложена многослойная сверточная нейронная сеть (MCNN), которая способна классифицировать листья яблони по одной из следующих категорий: парша яблони, черная гниль и болезни яблоневой кедровой ржавчины, используя недавно созданный набор данных. В этом методе мы использовали методы аффинного преобразования и перспективного преобразования для увеличения размера набора данных. После этого операции предварительной обработки на основе метода кадрирования и выравнивания гистограммы OpenCV использовались для улучшения предлагаемого набора данных изображения. Экспериментальные результаты показывают, что система достигает точности обучения 98,40% и точности проверки 98,47% для предложенного набора данных изображения с меньшим количеством параметров обучения. Результаты предполагают более высокую точность классификации предложенной модели MCNN по сравнению с другими известными современными подходами. Эта предложенная модель может использоваться для обнаружения и классификации других типов болезней яблони из разных наборов данных изображений.

Ключевые слова: искусственный интеллект, болезнь листьев яблони, обработка изображений, многослойная сверточная нейронная сеть, классификация.

Литература

1. А.И. Кузин, Н.Я. Каширская, Кочкина А.М., Кушнер А.В. Коррекция нормы калийной фертигации яблони (Malus domestica Borkh.) в средней полосе России в период вегетации // Растения. 9, нет. 10, с. 1366, октябрь 2020 г., doi: 10.3390/plants9101366.
2. Тай А.П.К., Мартин М.В. и Хилд С.Л. Угроза будущей глобальной продовольственной безопасности от изменения климата и загрязнения воздуха озоном // Nature Clim Change. 4, нет. 9, стр. 817–821, сентябрь 2014 г., doi: 10.1038/nclimate2317.
3. Р.Н. Стрэндж и П.Р. Скотт, «Болезни растений: угроза глобальной продовольственной безопасности», Annu. Преподобный Phytopathol., vol. 43, нет. 1. С. 83–116, сентябрь 2005 г., doi: 10.1146/annurev.phyto.43.113004.133839.
4. Аравинд К.Р., Раджа П., Мукеш К.В., Анируд Р., Ашивин Р. и Щепански К., «Классификация болезней кукурузы с использованием набора признаков и многоклассовой машины опорных векторов», 2-я Международная конференция

по изобретательским системам, 2018 г. and Control (ICISC), Coimbatore, январь 2018 г., стр. 1191–1196. doi: 10.1109/ICISC.2018.8398993.

5. В.П. Кур и С. Арора, «Машина опорных векторов на основе оптимизации роя частиц (P-SVM) для сегментации и классификации растений», IEEE Access, vol. 7, стр. 29374–29385, 2019, doi: 10.1109/ACCESS.2019.2901900.
6. М. Шейхан, М. Пежманпур, М.С. Мойн, «Улучшенный стегоанализ на основе контурлетов с использованием оптимизации роя бинарных частиц и радиальных нейронных сетей», Neural Comput & Applic, vol. 21, нет. 7, стр. 1717–1728, октябрь 2012 г., doi: 10.1007/s00521-011-0729-9.
7. Н. Геттари, А.С. Капелле-Лэиз и П. Карре, «Слепой стегоанализ изображений на основе доказательных K-ближайших соседей», Международная конференция IEEE по обработке изображений (ICIP), 2016 г., Феникс, Аризона, США, сентябрь 2016 г., стр. 2742–2746. doi: 10.1109/ICIP.2016.7532858.
8. Беди П. и Голе П. Обнаружение болезней растений с использованием гибридной модели на основе сверточных автоэнкодеров и сверточных нейронных сетей // Искусственный интеллект в сельском хозяйстве. 5, стр. 90–101, 2021, doi: 10.1016/j.aiia.2021.05.002.
9. С. Чакраборти, С. Пол и доктор медицинских наук Рахат-уз-Заман, «Прогнозирование болезней листьев яблони с использованием мультиклассовой машины опорных векторов», 2-я Международная конференция по робототехнике, электрическим технологиям и методам обработки сигналов (ICREST), 2021 г., Бангладеш, январь 2021 г., стр. 147–151. doi: 10.1109/ICREST51555.2021.9331132.
10. Ю. Чжун и М. Чжао, «Исследование глубокого обучения в распознавании болезней листьев яблони», Компьютеры и электроника в сельском хозяйстве, том. 168, с. 105146, январь 2020 г., doi: 10.1016/j.compag.2019.105146.
11. П. Йианг, Ы. Цхен, Б. Лиу, Д. Хе и Ц. Лианг, «Обнаружение болезней листьев яблони в реальном времени с использованием подхода глубокого обучения, основанного на улучшенных сверточных нейронных сетях», IEEE Access, vol. 7, стр. 59069–59080, 2019, doi: 10.1109/ACCESS.2019.2914929.
12. А.М. Хасан, Э. Агбозо, А.А.К. Аль-Саиди, С. Саха, А. Хайдари и М.Н.Ф. Раби, «Обнаружение опухоли головного мозга на изображениях МРТ с использованием методов обработки изображений», в 2021 г. 4-й Международный симпозиум по агентам, многоагентным Системы и робототехника (ISAMSR), Бату Пахат, Малайзия, сентябрь 2021 г., стр. 24–28. doi: 10.1109/ISAMSR53229.2021.9567799.
13. А.К. Рангараджан, Р. Пурушотаман и А. Рамеш, «Классификация болезней растений томатов с использованием предварительно обученного алгоритма глубокого обучения», Procedia Computer Science, vol. 2018. Т. 133. С. 1040–1047. doi: 10.1016/j.procs.2018.07.070.
14. Х. Хие, Ы. Ма, Б. Лиу, Дж. Хе, С. Ли и Х. Щанг, «Детектор заболеваний виноградных листьев в режиме реального времени на основе глубокого обучения с использованием усовершенствованных сверточных нейронных сетей», Front. Растениевод., т. 1, с. 11, с. 751, июнь 2020 г., doi: 10.3389/fpls.2020.00751.
15. Дж. Сан, Ы. Ыанг, Х. Хе и Х. Щу, «Обнаружение гнили листьев северной кукурузы в сложных полевых условиях на основе глубокого обучения», IEEE Доступ, том. 8, стр. 33679–33688, 2020, doi: 10.1109/ACCESS.2020.2973658.
16. Х. Саброл и К. Сатиш, «Классификация болезней растений томатов на цифровых изображениях с использованием дерева классификации», Международная конференция по связи и обработке сигналов (ICCSP) 2016 г., Мелмаруватур, Тамилнаду, Индия, апрель 2016 г., стр. 1242– 1246. doi:

10.1109/ICCSP.2016.7754351.

17. Д. Ядав, Аканкша и А.К. Ядав, «Новая модель на основе сверточной нейронной сети для распознавания и классификации болезней листьев яблони», TS, vol. 37, нет. 6, стр. 1093–1101, декабрь 2020 г., doi: 10.18280/ts.370622.
18. С. Баранвал, С. Ханделвал и А. Арора, «Сверточная нейронная сеть с глубоким обучением для обнаружения болезней листьев яблони», SSRN Journal, 2019, doi: 10.2139/ssrn.3351641.
19. Лю Б., Чжан Ю., Хэ Д., Ли Ю., «Идентификация болезней листьев яблони на основе глубоких сверточных нейронных сетей», Симметрия, том. 10, нет. 1, с. 11 декабря 2017 г., doi: 10.3390/sym10010011.
20. М. Керкеч, А. Хафиан и Р. Каналс, «Обнаружение болезней винограда на многоспектральных изображениях БПЛА с использованием оптимизированной регистрации изображений и подхода к сегментации глубокого обучения», Компьютеры и электроника в сельском хозяйстве, том. 174, с. 105446, июль 2020 г., doi: 10.1016/j.compag.2020.105446.
21. С.Л. Санга, Д. Мачуве и К. Джоманга, «Мобильные модели глубокого обучения для обнаружения банановых болезней», Eng. Технол. заявл. науч. Рез., том. 10, нет. 3, стр. 5674–5677, июнь 2020 г., doi: 10.48084/etasr.3452.
22. Факультет компьютерных наук, Университет Суккур IBA, Пакистан и др., «Обнаружение болезней растений с использованием глубокого обучения», IJRTE, vol. 9, нет. 1, стр. 909–914, май 2020 г., doi: 10.35940/ijrte.A2139.059120.
23. Л. Ву, Дж. Ма, Ю. Чжао и Х. Лю, «Обнаружение яблок в сложной сцене с использованием улучшенной модели YOLOv4», Агрономия, том. 11, нет. 3, с. 476, март 2021 г., doi: 10.3390/agronomy11030476.
24. С. Кулибали, Б. Камсу-Фогем, Д. Камиссоко и Д. Траоре, «Глубокие нейронные сети с переносом обучения на изображениях урожая проса», Компьютеры в промышленности, том. 108, стр. 115–120, июнь 2019 г., doi: 10.1016/j.compind.2019.02.003.
25. Брилл Ф., Ерухимов В., Гидутури Р., Рамм С., «Основные преобразования изображений», в Руководстве по программированию OpenVX, Elsevier, 2020, стр. 85–123. doi: 10.1016/B978-0-12-816425-9.00012-7.
26. С. Голлапуди, «OpenCV с Python», в книге «Изучение компьютерного зрения с помощью OpenCV», Беркли, Калифорния: Apress, 2019, стр. 31–50. doi: 10.1007/978-1-4842-4261-2_2.
27. Али Х., Лали М.И., Наваз М.З., Шариф М. и Салим Б.А. Автоматическое обнаружение болезней цитрусовых на основе симптомов с использованием цветовой гистограммы и текстурных дескрипторов // Компьютеры и электроника в сельском хозяйстве. 138, стр. 92–104, июнь 2017 г., doi: 10.1016/j.compag.2017.04.008.
28. Ю. Лекун, Л. Ботту, Ю. Бенжио и П. Хаффнер, «Градиентное обучение, применяемое для распознавания документов», Proc. IEEE, том. 86, нет. 11, стр. 2278–2324, ноябрь 1998 г., doi: 10.1109/5.726791.
29. Агарап А.Ф., «Глубокое обучение с использованием выпрямленных линейных единиц (ReLU)», arXiv: 1803.08375 [cs, stat], февраль 2019 г., доступ: 13 декабря 2021 г. [Онлайн]. Доступно: http://arxiv.org/abs/1803.08375
30. Антор Махмудул Хасан, «Болезни листьев яблони». Каггль. doi: 10.34740/KAGGLE/DSV/2068940.
31. Д.П. Кингма и Дж.Ба, «Адам: метод стохастической оптимизации», 2014 г., doi: 10.48550/ARXIV.1412.6980.
32. Р.Р.О. Аль-Нима, С.С. Длей, У.Л. Ву и Дж.А. Чемберс, «Новый биометрический подход к созданию ROC-кривой на основе вероятностной нейронной сети», 24-я конференция по обработке сигналов и связи (SIU), Зонгулдак, Турция, 2016 г.

Май 2016 г., стр. 141–144. doi: 10.1109/SIU.2016.7495697.

33. А. Хампария, Г. Саини, Д. Гупта, А. Ханна, С. Тивари и В.Х.К. де Альбукерке, «Прогнозирование и классификация сезонных болезней сельскохозяйственных культур с использованием сети глубоких сверточных кодировщиков», Circuits Syst Signal Process, vol. 39, нет. 2, стр. 818–836, февраль 2020 г., doi: 10.1007/s00034-019-01041-0.
34. Д. Тивари, М. Ашиш, Н. Гангвар, А. Шарма, С. Патель и С. Бхардвадж, «Обнаружение болезней листьев картофеля с использованием глубокого обучения», 2020 г. 4-я Международная конференция по интеллектуальным вычислительным системам и системам управления (ICICCS), Мадурай, Индия, май 2020 г., стр. 461–466. doi: 10.1109/ICICCS48265.2020.9121067.
35. Ф. Мохамет, К. Бинкай и К.А. Сада, «Обнаружение болезней растений с помощью глубокого обучения и извлечения признаков с использованием Plant Village», JCC, vol. 08, нет. 06, стр. 10–22, 2020, doi: 10.4236/jcc.2020.86002.
36. Ферентинос К.П. Модели глубокого обучения для обнаружения и диагностики болезней растений // Компьютеры и электроника в сельском хозяйстве. 145, стр. 311–318, февраль 2018 г., doi: 10.1016/j.compag.2018.01.009.

Махмудул Хасан Антор — Ph.D., помощник преподавателя, институт фундаментального образования, ФГАОУ ВО «УрФУ имени первого Президента России Б.Н. Ельцина» (УрФУ). Область научных интересов: интеллектуальные информационные технологии; проектирование, разработка и применение инновационных программных систем. Число научных публикаций — 7. mantor@urfu.ru; улица Мира, 19, 620002, Екатеринбург, Россия; р.т.: +7(962)316-1100.

Мд Ракиб Ул Ислам Ризу — студент, ФГАОУ ВО «УрФУ имени первого Президента России Б.Н. Ельцина» (УрФУ). Область научных интересов: глубокое обучение, машинное обучение. mdrakibulislam.rizu@urfu.me; улица Мира, 19, 620002, Екатеринбург, Россия; р.т.: +7(965)545-09-44.

Авинаш Кумар — студент, кафедра компьютерных наук, ФГАОУ ВО «УрФУ имени первого Президента России Б.Н. Ельцина» (УрФУ). Область научных интересов: глубокое обучение, машинное обучение. avinash.kumar@urfu.me; улица Мира, 19, 620002, Екатеринбург, Россия; р.т.: +7(919)397-64-01.